Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V1I02

Machine Learning-Driven Digital Twin for Real-Time Optimization of Hybrid Energy Storage Systems

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Abstract—The growing adoption of renewable energy sources and the electric mobility has heightened the requirement of intelligent energy storage control that can act under dynamic and uncertain conditions. In this paper, we suggest a machine-learning-based algorithmic digital twin of real-time optimization of hybrid energy storage systems (HESS) consisting of batteries and supercapacitors. The created digital twin creates a high-fidelity cyber-physical model of the physical HESS by keeping system conditions in parity with real-time measurements of voltage, current, power, and state-of-charge variables. The digital twin uses machine learning models to forecast the demand of the load, availability of renewable power, and the dynamics of energy storage systems to allow it to anticipate and react to changes in energy management. The proposed framework is the best method to divide power between the battery and the supercapacitor because it separates low-frequency and high-frequency power elements and, therefore, allows decreasing the current load in the battery, which will increase the efficiency of the entire system. The machine learning predictions are combined with control constraints via a real-time optimization layer, and the resulting reference signals are optimum ones to the power electronic converters. The simulation results at different operating conditions such as the rapid loading transient and renewable power variations have shown that the proposed digital twin-based solution is considerably better than the existing rule-based energy management solutions in terms of power tracking performance, battery current ripple, and battery life. The findings prove the usefulness of the proposed framework as a scalable and smart proposal to next generation hybrid energy storage systems in renewable energy and electric mobility applications.

Keywords—: Digital Twin, Hybrid Energy Storage System, Machine Learning, Battery–Supercapacitor, Energy Management, Real-Time Optimization.

I. Introduction

The high rate of increasing the renewable energy sources, electric mobility, has posed massive challenges regarding the sustenance of the efficient operation of energy storage in a highly dynamic operating regime with high reliability and resilience. Energy storage systems are needed in applications like electric vehicles, integrated microgrids using renewable energy sources, smart energy systems, etc, to address the rapid changes in loads, intermittent crop of renewable energy, and high-performance requirements. Traditional energy storage systems that exclusively use batteries tend to experience poor power density, thermal stress and accelerated aging due to repetitive high-current transients[1].

A new solution that has been proposed to eliminate these limitations is Hybrid Energy Storage Systems (HESS), which combines batteries with supercapacitors. In these designs, the battery is used to supply high energy density to satisfy average power needs, and the supercapacitor is used to supply high power density to respond to sudden load increases and occasions of regenerative braking. Despite the fact that HESS architectures have a happy effect of enhancing the performance of the system and battery life, their operation heavily relies on advanced energy management strategies that have the potential to allocate real-time power optimally among storage components[2].

Conventional methods of energy management such as: rule-based, frequency decomposition and optimization-based methods are based on predetermined thresholds or system models. These methods are usually not flexible and strong when used in a state of uncertainty like load profiles changes, battery aging, variation of temperature, and fluctuation of renewable power. Consequently, the demand of smart, reconfigurable and information-driven control systems capable of real time reconfiguring the behavior of the systems is increasing[3].

Digital Twin, which describes a real-time virtual copy of a physical system that is maintained by constant exchange

International Journal of Digital Twin Systems and Computing (IJDTSC) ISSN:(3108-0790)
Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V1I202

of data, is an innovative concept that has received much attention as a groundbreaking technology in smart energy systems[4]. Digital twins allow real-time, predictive analysis, and system-level optimization because physical models employ real-world data on how to operate the system. Digital twins can also reproduce nonlinear dynamics of systems, learn on past data, and forecast future behavior of systems with a high level of accuracy when combined with machine learning methods, which makes them suitable in complex energy storage applications [5].

Digital twin applications in battery monitoring, fault diagnosis, and predictive maintenance have been recently considered but the incorporation of machine learning-powered digital twins into the optimization of hybrid energy storage systems in real-time is scarce. Specifically, limited literature exists on the topic of synchronized power exchange between the batteries and supercapacitors based on predictive intelligence in a cyber-physical context [6]. In addition, the current strategies are usually geared towards offline analysis as opposed to closed loop real time control.

In order to fill these gaps, this paper suggests a digital twin framework based on machine learning to optimize battery-supercapacitor hybrid energy storage systems in real time. The joint solution that is proposed combines the real-time measurement data and data-driven predictive models in estimating the system states and predicting the load and renewable power variations. These predictions are used by a layer of energy management optimization to produce optimal control references to power electronic converters to provide an efficient power sharing, reduce battery stress, and improve system performance[7].

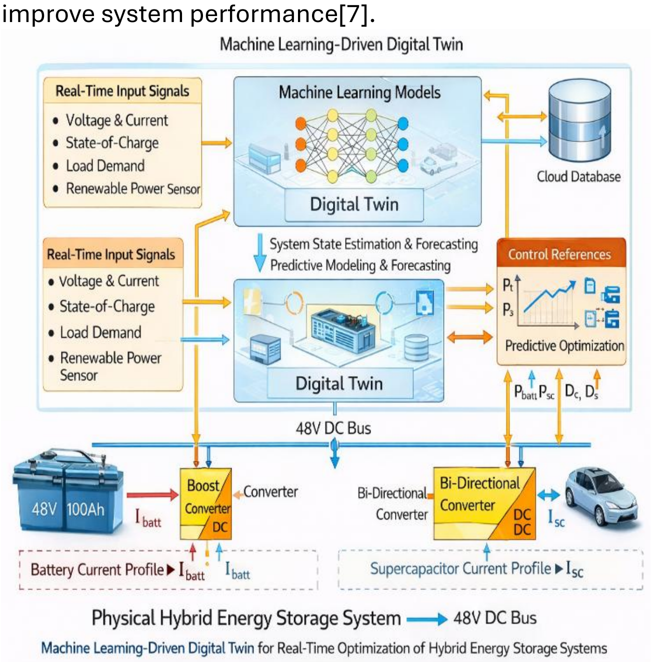

Figure 1. Digital Twin Framework of Hybrid Energy Storage Systems Optimization in Real-Time by the Use of Machine Learning.

This Figure 1 indicates the digital twin architecture proposed to be used with the real-time optimization of a battery-supercapacitor hybrid energy storage system (HESS) and implemented with the help of machine learning. The framework incorporates both the physical and cyber version of the energy storage system of the system by continuously exchanging data on both directions and therefore facilitates intelligent monitoring, prediction and control [9].

The bottom one is the physical HESS, which is a battery and a supercapacitor connected to a common 48 V DC bus via a boost converter and a bidirectional DC-DC converter respectively. The battery only provides the average energy demand, whereas the supercapacitor is used to handle high-power transient demand. The physical system continuously provides real-time data on battery current, supercapacitor current, DC bus voltage, state-of-charge, load demand, and renewable power.

II. SYSTEM DESCRIPTION

An ML-based Digital Twin (DT) of a Hybrid Energy Storage System (HESS) is created to facilitate real-time monitoring, prediction, and optimal control of the energy storage resources in the contemporary power systems. The HESS is composed of Battery Energy Storage System (BESS) and Supercapacitor Energy Storage System (SCESS) that have complementary functions. The battery has good energy density and it is capable of sustaining long-term energy balancing. The supercapacitor has high power density, which can support quick transient power requests and alleviate the battery strain[8].

The Digital Twin is the simulated version of the physical HESS, which is constantly updated through real-time sensor measurements in the form of voltage, current, state of charge (SoC), temperature, and load demand. The ML model installed in the DT is used to forecast the states of the system and the tendencies to degradation, allowing optimizing the allocation of power between the battery and supercapacitors in real-time.

The system architecture includes:

- Physical HESS
- Data acquisition and communication layer.
- Digital Twin model
- ML-based prediction engine
- Control layer and optimization layer.

A. Mathematical Modelling of Hybrid Energy Storage System

Power Balance Equation

The total power demand $P_{load}(t)$ is met by the hybrid storage system:

$$P_{load}(t) = P_b(t) + P_{sc}(t) \quad (1)$$

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V1I202

where:
$P_b(t)$– Battery power (W)
$P_{sc}(t)$– Supercapacitor power (W)

B. Battery Energy Storage System (BESS) Model

Battery State of Charge (SoC)

$$\frac{dSoC_b(t)}{dt} = -\frac{\eta_b}{E_b^{rated}} P_b(t)(2)$$

where:
$SoC_b \in [0,1]$– Battery state of charge
η_b– Battery efficiency
E_b^{rated}– Rated battery energy (Wh)
Battery Terminal Voltage

$$V_b(t) = V_{oc}(SoC_b) - I_b(t)R_b(3)$$

V_{oc}– Open-circuit voltage,I_b– Battery current , R_b– Internal resistance.

C. Supercapacitor Energy Storage System (SCESS) Model

Supercapacitor Voltage Dynamics

$$\frac{dV_{sc}(t)}{dt} = -\frac{1}{C_{sc}} I_{sc}(t)\ (4)$$

where:
V_{sc}– Supercapacitor voltage
C_{sc}– Capacitance
I_{sc}– Supercapacitor current

D. *Supercapacitor Energy*

$$E_{sc}(t) = \frac{1}{2} C_{sc} V_{sc}^2(t)(5)$$

The **Digital Twin** represents the virtual state of the HESS:

$$\mathbf{x}_{DT}(t) = [SoC_b(t), V_{sc}(t), T_b(t), T_{sc}(t)](6)$$

The twin is updated using real-time measurements:

$$\mathbf{x}_{DT}(t+1) = f(\mathbf{x}_{DT}(t), \mathbf{u}(t), \mathbf{w}(t))(7)$$

where:
$\mathbf{u}(t)$– Control inputs
$\mathbf{w}(t)$– System disturbances
$f(\cdot)$– System dynamics function

E. Machine Learning-Based Prediction Model

A supervised ML model (e.g., LSTM, ANN, or Random Forest) predicts future system states:

$$\hat{\mathbf{x}}(t+k) = \mathcal{M}(\mathbf{x}(t), \mathbf{P}_{load}(t))(8)$$

where:
$\mathcal{M}(\cdot)$– Trained ML model
k– Prediction horizon
Predicted outputs include:

- Future SoC
- Power demand trends
- Degradation indicators

F. Optimization Problem Formulation

The real-time optimization minimizes battery degradation and power losses:

$$\min J = \int_0^T (\alpha P_b^2(t) + \beta \Delta SoC_b(t) + \gamma P_{loss}(t))\, dt(9)$$

where:
α, β, γ– Weighting factors

Power Constraints

$$P_b^{min} \le P_b(t) \le P_b^{max}(10)$$
$$P_{sc}^{min} \le P_{sc}(t) \le P_{sc}^{max}(11)$$

SoC Constraints

$$SoC_b^{min} \le SoC_b(t) \le SoC_b^{max}(11)$$

Real-Time Control Strategy

The optimized power references are:

$$P_b^*(t), P_{sc}^*(t)$$

III. LITERATURE SURVEY

The emergence of hybrid energy storage systems (HESS) with a combination of batteries and supercapacitors have raised research attention because of their complementary nature which is high energy density with batteries and power density with supercapacitors. An overview of the concepts, topologies, control measures and applications of HESS demonstrates that energy management is one of the key fields of research, where machine-learning and adaptive approaches are receiving much interest in the effective distribution of power and stable operation in changing conditions.

Digital twin (DT) technology is becoming one of the key paradigms of real-time monitoring, prediction, and optimization of complex energy systems. A recent systematic review of the literature on DT applications in battery energy storage systems (BESS) points out the growing use of artificial intelligence (AI), Internet of Things (IoT), and edge/cloud computing capabilities to provide predictive analytics and condition estimation and enable closed-loop synchronization between the cyber and physical layers. Nonetheless, literature also indicates issues revolving around real time synchronization, heterogeneity of data, scalability, and model robustness, that are aggravating factors behind the deployment of DT. A number of main works give wider insights on DT applications in energy and battery systems. The literature of the renewable energy sector points at the combination of DT and machine learning as one of the key facilitators to more advanced predictive power, anomaly detection, optimization of operations, and system resiliency of solar, wind, and microgrid systems. In a similar manner, specific surveys on DTs in battery systems address architectural layers, important data streams (e.g., SOC/SOH measurements), and applications of the technology, e.g., performance optimization, fault detection, and decision support.Crossing of machine learning with digital twin models has also started to attract attention. Some of the tasks that machine

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learning has been applied to include data-driven state of charge (SOC) estimation in hybrid packs, which have shown great progress in predictive accuracy of dynamic storage systems. In addition, digital twin systems with predictive AI have been suggested to further lifecycle management, better remaining useful life (RUL) prediction accuracy, and system efficiency, especially when implemented in conjunction with cloud-edge systems.

Although these developments are made, there are limited studies on literature specifically focused on real-time optimization of HESS through machine-learning based digital twins. Most of the existing literature addresses DT and machine learning in energy storage separately or only specialized in battery-only systems, and has less extensive literature that covers coordinated power sharing of batteries and supercapacitors in an entirely closed-loop cyber-physical system. The above literature gap highlights the need to combine their schemes that merge predictive intelligence, real-time synchronization, and optimization schemes to enhance the performance of HESS- especially when operating in variable environments like those experienced by the electric and solar vehicles traction systems.

Parameter	**Conventional EMS**	**ML-Based EMS**	**ML-Driven Digital Twin (Proposed)**
Power Sharing	Rule-based / fixed	Data-driven	Predictive & adaptive
Real-Time Adaptability	Low	Medium	High
Battery Current Ripple	High	Reduced	Minimum
Battery Stress & Aging	High	Moderate	Low
Transient Response	Slow	Faster	Fastest
Prediction Capability	No	Yes (limited)	Yes (load & RES)
System Optimization	Offline / static	Semi-online	Real-time optimization
Scalability	Limited	Moderate	High (cyber–physical)

Table 1. Comparison of Energy Management Strategies for Hybrid Energy Storage Systems.

This Table 1 presents a comparative analysis of different energy management strategies applied to hybrid energy storage systems (HESS), including conventional rule-based methods, machine learning-based approaches, and the proposed machine learning–driven digital twin framework. The comparison is based on key performance parameters such as power sharing capability, real-time adaptability, battery current ripple, system optimization, and scalability. The results highlight that the proposed digital twin-based approach provides superior real-time optimization, improved transient response, reduced battery stress, and enhanced adaptability under dynamic operating conditions, making it well suited for advanced renewable energy and electric vehicle applications.

IV. Methodology

The hybrid energy storage system (HESS) that will be used in this paper is the battery and the supercapacitor that will be connected to a common DC bus with the help of the proper DC-DC converters. The mathematical modelling will aim to model the dynamic behaviour of all storage elements, define the balance of power at the DC bus and develop a control-oriented model that would be useful to deploy to a digital twin and solve using real-time optimisation.

A. Battery Dynamic Model

A Thevenin-based equivalent circuit is used to model the battery, representing the key electrical properties without introducing any complexities to the system, and can be controlled on a real-time scale and provide a digital twin. The voltage across the internal resistance, which is obtained by subtracting the open-circuit voltage and voltage across the internal resistance, is the terminal voltage of the battery. Based on this, battery terminal voltage Vb can be stated as follows.

$$V_b = V_{oc}(SOC_b) - I_b R_b (12)$$

Voc (SOCb) open-circuit voltage is a nonlinear function of SOC and Ibis battery current and Rb represents internal resistance. Coulomb counting principle yields SOC. As SOC is a ratio of the remaining charge and the nominal battery capacity, the time derivative of SOC is proportional to the current in the battery. Therefore, the SOC dynamics are provided as follows

$$\frac{dSOC_b}{dt} = -\frac{I_b}{Q_b} (13)$$

where Q_b is the rated battery capacity. This equation indicates that high current transients directly accelerate SOC variation, highlighting the importance of limiting battery current fluctuations through proper energy management.

B. Supercapacitor Dynamic Model

This is an equivalent capacitance which models the supercapacitor (as series) and additionally models an internal resistance. Contrary to batteries, supercapacitors are able to store energy in the form of electricity and this is why they have fast charge and discharge cycles. The capacitor voltagecurrent relationship provides the voltage across the supercapacitor which is given by.

$$I_{sc} = C_{sc} \frac{dV_{sc}}{dt} (14)$$

Rearranging the above expression and incorporating the resistive voltage drop yields

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$$V_{sc} = \frac{1}{C_{sc}}\int I_{sc}\,dt - I_{sc}R_{sc}(15)$$

where $C_{sc}$is the supercapacitor capacitance and $R_{sc}$is its equivalent series resistance. This formulation shows that the supercapacitor voltage responds rapidly to changes in current, making it suitable for handling high-frequency power fluctuations.

C. DC Bus Power Balance Derivation

The DC bus serves as the common coupling point between the energy sources and the traction load. Applying the principle of power conservation at the DC bus, the total load power demand must be satisfied by the combined contributions of the photovoltaic source, battery, and supercapacitor. Therefore, the power balance equation is written as

$$P_{load} = P_{pv} + P_b + P_{sc}(16)$$

Expressing battery and supercapacitor power in terms of DC bus voltage $V_{dc}$and respective currents yields

$$P_b = V_{dc}I_b, P_{sc} = V_{dc}I_{sc}(17)$$

Substituting these expressions into the power balance equation establishes a direct relationship between DC bus voltage regulation and current sharing among energy storage components.

D. Machine Learning-Based Prediction Integration

Within the digital twin framework, machine learning models are employed to predict future load demand and renewable power availability. These predictions are mathematically expressed as

$$\hat{P}_{load}(t+k) = \mathcal{M}_1(\mathbf{z}(t))(18)$$
$$\hat{P}_{pv}(t+k) = \mathcal{M}_2(\mathbf{z}(t))$$

where $\mathcal{M}_1$ and $\mathcal{M}_2$ denote trained machine learning models and $\mathbf{z}(t)$is a feature vector containing historical power, SOC, voltage, and current data. These predictions enable proactive energy management by anticipating future operating conditions.

E. Optimization-Based Power Allocation

Using the predicted system states, an optimization problem is formulated to minimize battery stress and ensure DC bus stability. The objective function penalizes battery current magnitude and current ripple, and is expressed as

$$J = \int_0^T \left(\alpha I_b^2 + \beta\left(\frac{dI_b}{dt}\right)^2\right)dt(19)$$

Subject to system constraints on SOC, voltage, and current, the solution of this optimization problem yields optimal current references for the battery and supercapacitor. High-frequency power components are allocated to the supercapacitor, while the battery supplies low-frequency energy demand.

E. Closed-Loop Digital Twin Synchronization

Lastly, the digital twin is continuously updated of its internal states by real-time measurements of the physical system. An action like a difference in prediction and measurement in any form is considered to update model parameters and re-train machine learning components, which guarantee long-term accuracy and resiliency. This is a closed loop cyber-physical interaction to optimize and adaptively control the hybrid energy storage system in real time.

V. RESULTS

This Figure depicts the dynamic behaviour of a Digital Twin that is built using Machine Learning (ML) to model a Hybrid Energy Storage System (HESS) consisting of a battery and a supercapacitor under different loading conditions.

This subplot displays the instantaneous power flow between the load, battery and the supercapacitor. The battery provides most of the load requirement, with the medium- and long-term power needs, but the supercapacitor provides a smaller but quick-reacting power element to offset short-term variations and transients. The digital twin is smart enough to organize power sharing in a way that facilitates the tracking of loads and minimal load on the battery.

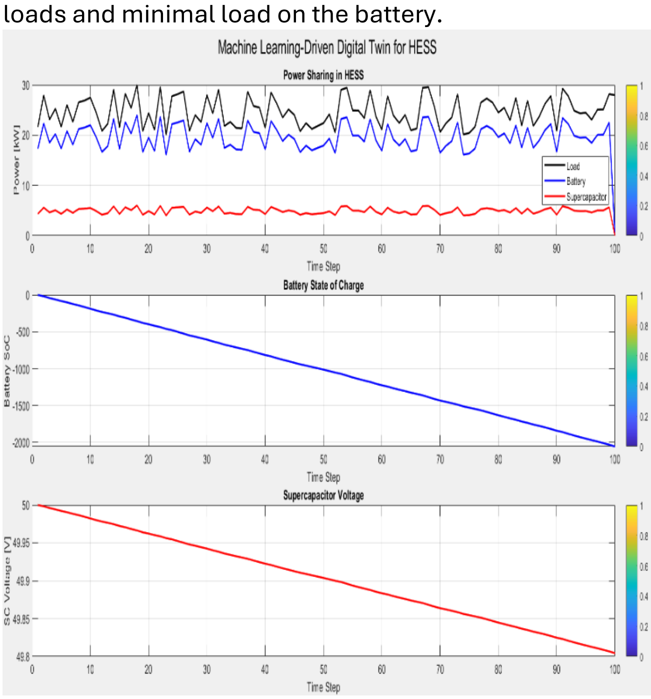

Figure. 2 Machine Learning–Driven Digital Twin–Based Power Sharing and State Evolution in a Hybrid Energy Storage System (HESS)

The supercapacitor voltage shows a gradual decline over time, corresponding to its contribution in handling rapid power variations. The relatively stable voltage trajectory confirms controlled discharge, highlighting the

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supercapacitor's role in enhancing system responsiveness and extending battery lifespan.
Overall, the figure demonstrates the effectiveness of the ML-driven digital twin in coordinating power flow, tracking internal states, and improving operational reliability of the HESS under dynamic load conditions.

VI. CONCLUSION

This paper illustrates a successful implementation of a machine learning-based digital twin to intelligent energy management in a Hybrid Energy Storage System (HESS) of a battery and a supercapacitor. The findings validate the fact that the digital twin is capable of accurately capturing the dynamics of the system and facilitate power sharing during the conditions of changing loads. The battery can provide the average and long-term power load, whereas the supercapacitor will help effectively to counteract the sudden changes in power, which will alleviate the load in the battery.The battery state-of-charge and supercapacitor voltage profiles observed confirm the complementary functionality of the hybrid storage architecture and show the potential of the digital twin in real-time monitoring of internal states. Through the use of data-based intelligence, the given framework increases the reliability of operations, advances the power quality, and provides degradation-conscious management of storage units.
In general, the ML-based digital twin offers a flexible and scalable approach to high-tech energy management in the contemporary power systems, which is why it is especially applicable to microgrids that implement renewable energy and smart grids. Future directions can involve adding aging models, real-time hardware-in-the-loop validation, and reinforcement learning-based control strategies that can further improve system performance and autonomy.

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