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Deep learning based digital twins augmented reality: Model predictive control for battery and storage optimization in renewable energy prosumers districts

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ABSTRACT

In modern energy systems, integrating renewable energy sources has accelerated the development of prosumer networks, where entities produce and consume energy. The inherent variability of renewable generation challenges maintaining a balance between supply and demand. Optimizing battery and storage systems is required to overcome this volatile behavior of renewable generation to ensure energy and cost efficiency. This paper proposes a Deep Learning-Driven Model Predictive Control (DL-MPC) framework that uses Digital Twin (DT) and Augmented Reality (AR) technologies to optimize energy storage in prosumer districts. The framework utilises the DL model for energy and consumption forecasting for MPC to adjust energy storage and distribution in real-time dynamically. The DT technology emulates the real-time prosumer district to generate feedback for continuous improvement of the control decisions. Moreover, the AR interface provides an intuitive view of the real-time energy flow, storage levels, and usage statistics to improve decision-making and inform immediate adjustments. The proposed DL-MPC framework is simulated using real-world data. The framework improves 15 % energy efficiency and reduces 20 % operational cost in comparison to traditional methods. This framework presents a robust, scalable, adaptive tool to optimize the energy flows in modern power grids.

1. Introduction

The rapid adoption of renewable energy sources (RESs) is reshaping the landscape of modern power grids, a transition from fossil-fuel-based to diverse and variable energy sources [1,2]. This shift introduces the concept of prosumers, who produce and consume energy from the power grid. The dual mode of prosumers formulates the concept of bidirectional energy flow [3]. Managing bidirectional energy requires new strategies for energy balance between supply and demand. Optimal energy dispatch strategies are particularly critical in distributed energy systems, such as microgrids, to manage renewable variability and achieve low-carbon operation under constraints like electricity supply restrictions [4]. The volatile nature of renewable energy poses sustainable challenges to managing intermittent energy sources as weather conditions and climatic drifts influence the RES demand [5].

To ride through these variations and maintain a steady energy supply, energy storage systems, especially batteries, have become crucial. They are ideal for buffering supply-demand balances as the batteries can absorb excess electricity when production is high and release it when production falls [6,7]. However, efficiently orchestrating these storage systems is key to maximizing the penetration of RESs, reducing imported power from the grid, and improving the overall resilience of the energy system. Conventional methodologies for storage management grounded on rule-based/static control schemes are inadequate for addressing the dynamic/infrequent nature of these prosumer-based energy networks. Since renewable energy systems are highly dynamic, these approaches often lack responsiveness to sudden energy generation and/or demand bursts [8,9]. Therefore, the perfect control solution should be intelligent, adaptable to real-time conditions, and optimized for energy storage [10,11].

The combination of Model Predictive Control (MPC) and Deep Learning (DL), in particular, has proven effective at solving energy storage problems in renewable energy networks in recent years [12–15]. MPC is a broadly utilized optimisation methodology frequently

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employed in control systems facing constraints and long-term challenges [16]. In the energy storage context, MPC is used to optimize the control actions by predicting future states of a dynamic system over a specific time horizon and ensuring the energy is stored or dispatched to meet anticipated demands. The effectiveness of MPC, however, depends on the efficacy of its prediction models [17,18]. In a more complex system based on RESs, traditional MPC, which assumes linearity, will no longer be effective due to the non-linearity of RES generation and consumption patterns.

DL addresses this limitation and can deal with complex and non-linear relationships in the data, thereby improving the predictive capability of a given MPC [15]. Considering time series data from the past and real-time, deep learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, enhance the performance in pattern recognition and accurate prediction of future energy needs and provision [19,20]. This allows the control system to respond to changing energy conditions by using all the information available so that, by combining DL and MPC, more adaptive, better, and informed decisions are taken. Such a combination of DL and MPC allows a battery storage management system that optimizes battery operation for high energy efficiency while meeting grid demand and prosumers' requirements [21].

Integrating Digital Twin (DT) technology is a major innovation in this framework. A DT is a real-time representation of a living or nonliving physical entity [22]. In a renewable energy prosumer network, the entire energy ecosystem is modelled in the DT, including generation sources, storage systems, and consumption patterns. Due to the mirroring of the physical energy network, the DT allows operators and the control system to monitor, predict, and optimize the energy flows (with high accuracy). The DT can predict future state(s), run what-if scenarios, and recommend the best way to store data through ongoing data feedback and simulation [23]. By employing the DL-MPC framework, adjustments can be made, which will help the system reach a more stable and efficient equilibrium, and the real-time virtual model of the prosumer district contributes to managing the prosumer district with greater precision.

Further, the implemented Augmented Reality (AR) interface improves the user's engagement with the digital twin model [24]. The AR interface offers prosumers and operators an immersive, interactive visualization of real-time energy flows, storage levels, and usage statistics. Using AR, users can view in-depth information on the energy system, thus making informed decisions on storage and consumption in real or near real-time. Such a user-centric, interactive interface enhances situational awareness. It enables a more participatory approach to energy management, where prosumers and grid operators can work hand in hand to make joint decisions that optimize grid stability and personal energy goals [25].

A DT and AR-based DL-MPC framework is proposed in this paper to optimize the management of batteries and storage systems in renewable energy prosumer neighbourhoods. It uses DL's predictive ability to inform the MPC's response to varying renewable generation and demand. This DT is a perpetual, time-evolving model of the energy ecosystem to which the DL-MPC framework can continually adapt, tailoring its control strategies to reflect current and predicted conditions. Real data-based simulation results indicate that this integrated approach significantly improves energy efficiency and economic performance. This system addresses the limitations of traditional storage management approaches, achieving 15 % improvements in energy efficiency and 20 % reductions in operational costs.

The proposed framework is a robust, scalable approach for optimizing renewable energy storage in the prosumer network. This overcomes the inherent challenges of renewable energy by harnessing the predictive power of DL with the adaptive control of MPC and the real-time simulation of DTs. This supplemental AR layer is a powerful interface for visualization, feedback, and control, giving the user the perception needed to oversee and effectively navigate increasingly decentralized energy systems. This mechanism lays the foundation for intelligent and resilient prosumer networks, propelling renewable energy in sustainable and distributed energy grids.

The key contributions of our work are enumerated as follows:

- Deep Learning-Driven MPC for Greater Prediction Accuracy: This paper focuses on improving the prediction accuracy in prosumer networks for energy demand and generation through DL models in the MPC architecture. Further, this integration allows the system to accommodate complex, non-linear relationships in the data, improving its forecast model of renewable energy availability and consumption patterns.
- Adaptive, Real-Time Optimization via Digital Twin Integration: A DT of the prosumer network allows our system to continuously mimic real-world operations, aligning with current state dimensions and enabling real-time feedback to optimize the flow and storage of energy proactively. Hence, the system focuses on minimizing the dependency on grid energy by optimizing storage discharging at the time of energy use and charging it as and when required as per the real-time scenarios, thus providing better energy performance and reducing operation costs.
- Augmented Reality Feature for Enhanced User Interaction and Decision-Making: To make the system more useful, we add an AR interface to view the energy consumption during the day, the energy storage levels, and the energy metrics. It provides insight for on-the-spot decision-making and tweaks, leading to a more cooperative, informed approach to energy management.
- Efficient Design for Distributed Renewable Energy Systems: The proposed framework is efficient and can be implemented at a large scale in residential prosumer districts and industrial or commercial energy metering. The system proposed by the researchers addresses the unique needs of renewable energy prosumer networks. It provides a model for sustainable, decentralized energy management systems that can grow with improvements in renewable technologies.

The remainder of the paper is structured as follows. Section 2 presents a detailed literature review of MPC, DT, and DL for energy forecasting. A real-time energy optimisation system is presented in Section 3 that combines DL-enhanced MPC, DT technology and AR. Section 4 formulated the mathematical modelling of the proposed methodology. Section 5 presents the performance analysis of DL-MPC using various performance metrics. Section 6 concludes the paper with a summary and future directions.

2. Literature review

2.1. MPC for battery and storage optimisation in renewable energy systems

Given the predictive nature of MPC and a robust optimization framework under system constraints, ample algorithm application exists in the energy domain [26]. MPC is useful in optimizing battery and storage systems in renewable energy systems, particularly in managing energy exchange between the generation, storage, and load systems. This is especially useful for prosumer districts of renewable energy, where the volatile nature of energy generation (e.g., solar, wind) can induce fast changes in supply-demand relations [27]. MPC can factor in the predictability of uneven energy production and adjust storage operations accordingly, thus flattening these fluctuations and improving system stability and efficiency [28]. Traditional MPC is mainly based on linear or quasi-linear models, which can hardly fully capture the non-linear dynamics of the renewable energy system. Moreover, proper implementation of MPC relies on correct forecasts for future energy demand and supply, a difficult problem in prosumer networks, considering the stochastic nature of renewable sources and consumer behaviors [29]. Recent works have examined ways to combine MPC and machine learning for improved prediction accuracy within MPC setups, focusing especially on advancements rooted in deep learning [30]. Our approach entails using deep learning models for forecasting, which allows MPC to make real-time adjustments to the battery and storage systems using accurate predictions of energy generation, storage, and demand. This study fuses deep learning into MPC to overcome the hurdles of the traditional MPC in enhancing battery optimisation for renewable energy systems.

Recent advancements in distributed energy systems highlight the critical need for optimal energy dispatch strategies to manage the complexity of renewable-based microgrids. For example, [31] proposed a commercial operational model for a shared energy storage system that improved the integration of renewable energy plants by allowing profit based on end-users' contributions and energy transactions. The sharing model incorporated dynamic battery degradation modelling that increased system efficiency, improved market participation and economic viability of renewable power plants. A bi-level optimization model was proposed for a battery energy storage system using an optimal bidding strategy that maximized benefits considering market prices [32]. A demand response strategy is developed for grid-connected energy storage systems to increase the power system stability and efficiency, resulting in active participation of end users in grid management [33]. The proposed strategy reduced peak loads and dealt with the increased demand and intermittency associated with renewable energy. A decentralized dispatch approach is proposed for distributed PV systems, achieving 15–20 % cost reduction and 25–30 % improved renewable utilization in next-generation distribution management systems [4]. Their work underscores challenges such as variable generation, grid stability, and the demand for real-time, scalable algorithms, which traditional methods struggle to address due to limited adaptability and high computational costs. These findings emphasise the need for advanced computational frameworks, such as those integrating deep learning and real-time control, to optimize energy flows in prosumer networks, motivating the present study's DL-MPC approach.

2.2. *Digital Twin technology in renewable energy prosumers*

DT represents a technology growing in popularity in fields as diverse as smart grid and renewable energy, as it creates a virtual representation of a physical entity or system. By providing real-time feedback on the physical system, DTs can enable monitoring, simulation, and optimisation of energy assets closely and continuously, making them suitable for the dynamic interactions in renewable energy prosumer networks. In networks where consumers are also energy producers, DTs represent a useful tool to emulate and simulate real-time generation, storage, and consumption behavior. With such capability, the system can predict and respond to shifts in demand while maximizing energy collection and use with cycle avoidance, ensuring continuity of operations [22].

In renewable energy systems, DTs enable operational flexibility by allowing operators to model control strategies and test improvements before they enter the physical grid. DT enables real-time data collection on energy generation, storage levels, load demands, and user behaviors for battery and storage optimization. The Digital Twin model presented in this study aids the DL-MPC framework by constantly mirroring the physical energy network, offering a dynamic stage for real-time optimization. DT empowers the system to mimic diverse storage management practices, evaluate their impact on system stability, and implement informed modifications as conditions change. Our work adds to the literature on DTs in renewable energy by showing their alignment with advanced control techniques for efficient and fast energy management at the prosumer level [23].

2.3. *Deep Learning for forecasting in renewable energy storage management*

DL is rapidly adopted as the approach of choice for forecasting the demand for energy supply and storage in renewable energy systems and is especially useful for forecasting the highly volatile and non-linear demand patterns in prosumer networks [34,35]. However, existing techniques (e.g., time-series approaches) rarely incorporate complex interdependencies of interrelated energy processes in the model, limiting their ability to manage variable energy flow from renewable sources. Deep learning methods like CNNs and LSTM networks enable advanced analysis of energy data's complex temporal and spatial dependencies [20]. This ability makes them a good candidate for prediction in renewable energy prosumer networks, where consumption and generation can change rapidly and cannot be easily predicted.

This paper presents an implementation of a DL-MPC framework, which is trained on historical and real-time datasets (prosumer network) outputs, generation, storage, and demand. The model is trained to make predictions that include weather data, time of day, and seasonality, which is fed to the MPC framework and achieves highly accurate predictions. Ultimately, this allows the DL-MPC system to preemptively optimize battery and storage operations to achieve energy efficiency gains and reduce dependence on the grid. A recent review identified this integration of a predictive model into a real-time control framework for storage optimization as an untapped area of research in deep learning for energy forecasting, which will aid in energy management within renewable energy prosumer networks.

2.4. *Shortcomings of related work*

Limited Accuracy in Predictive Modelling: Conventional MPC controllers are based on linear or quasi-linear models that are often inadequate in representing the intricate non-linear behaviors of renewable energy systems. These models fail to capture the uncertainty presented by prosumer networks, which leads to less accurate control and optimization.

Static Forecasting Methods: Existing forecasting methods (e.g., time-series models) rely on linear assumptions but often fail to adapt to real-time shifts. These approaches overlook the variability and complexity in prosumer networks driven by dynamic elements such as weather conditions, seasonal insights, and user behavior. Hence, these systems are not responsive enough for efficient energy storage optimization.

Lack of Real-Time Adaptability: Many current systems are not designed to operate in real-time and thus cannot respond effectively to rapid fluctuations in energy supply and demand. Static rule-based or heuristic systems cannot automatically optimize storage operations over time without continuous updates, leading to grid power dependence.

Underutilization of Digital Twin Technology: While DT technology has demonstrated promise for energy systems, its integration with advanced control and optimization frameworks remains limited. Most available implementations of Digital Twins for energy systems focus mainly on monitoring instead of proactive control. This leads to a lack of real-time adaptive solutions for optimization in prosumer networks.

Weighed-down Siloed Approaches Lacking Integrated Control Framework: Although some approaches aggregate individual technologies (e.g., deep learning for forecasting or MPC for control), none integrates them with Digital Twins into a unified structured sales method. By failing to integrate data, there is little opportunity for predictive, real-time optimization of prosumer networks.

2.5. *Integrating Deep Learning, Digital Twin, and MPC for proactive energy management*

As a result, merging DL, DT technology, and MPC forms a potent approach toward optimizing battery and storage systems within prosumer networks, harnessing renewable energy sources. Combining the predictive power of DL, the real-time optimisation capabilities offered by MPC, and the real-time intelligence of the DT, this solution creates a dynamic system responsive to the changing nature of energy. This framework thus anticipates losses and mitigation by simulating various control strategies in the DT environment, thereby improving energy storage cell management and overall resilience.

This paper is novel in that it focuses on how these technologies can work in tandem, which is significantly more effective than the traditional, disparate approaches to energy management. Our method enhances the Digital Twin-based energy model by using MPC to represent it, which allows for integrating deep learning predictions to create a much more resilient and proactive system. This work contributes to the emerging renewable energy optimization space by designing a scalable grid, considering the dynamic nature of a prosumer network.

3. System architecture

The system architecture comprises the DT, DL model, MPC framework, and AR interface. These components facilitate optimal energy storage and distribution in renewable energy prosumer districts. The DT model design for DL with MPC optimization for battery storage is shown in Fig. 1. Built for AR, the system is intended to empower users, flow even more energy back to the grid, and simplify decentralized energy resource management following the unpredictable behavior of RESs.

3.1. *Digital Twin integration*

Central to the architecture is the DT, a real-time virtual replica of the physical prosumer network. The DT replicates the entire energy ecosystem, from the energy generated by RESs (solar panels), battery storage systems, and energy district consumption. These models reflect the realities of the operating conditions and are updated continuously in real whilst, on the power side, this virtual twin integrates data from the physical energy system. From various sensors and smart meters embedded in the prosumer network, the DT gathers data on key metrics, including energy generation rates, battery charge/discharge cycles, grid energy imports, and user consumption behavior. This crucial information enables the DT to assess the system's future behavior, anticipate the forthcoming states, and recommend advisable control methods. The MPC framework, driven by the DT, models and analyses the energy flows in the prosumer district, allowing it to make informed data-driven decisions and optimize energy usage within the eco-district. Further, the DT can execute scenario-based simulations, which enable the operators and the MPC framework to evaluate several energy management strategies under diverse operating conditions, like variations in solar irradiance and changes to energy demand. This ability to provide real-time feedback and simulate how the system will react as time is critical, ensuring that the system automatically adjusts to changing energy conditions.

3.2. *Deep Learning model for predictive forecasting*

The DL model is essential for predicting upcoming energy needs and availability within the prosumer grid. The DL model is trained using historical data and recent inputs to predict energy generation and consumption trends over short and long-time horizons. With neural network architectures like LSTMs and CNNs, the model captures complex and non-linear relationships in the energy data. The DL model takes a stream

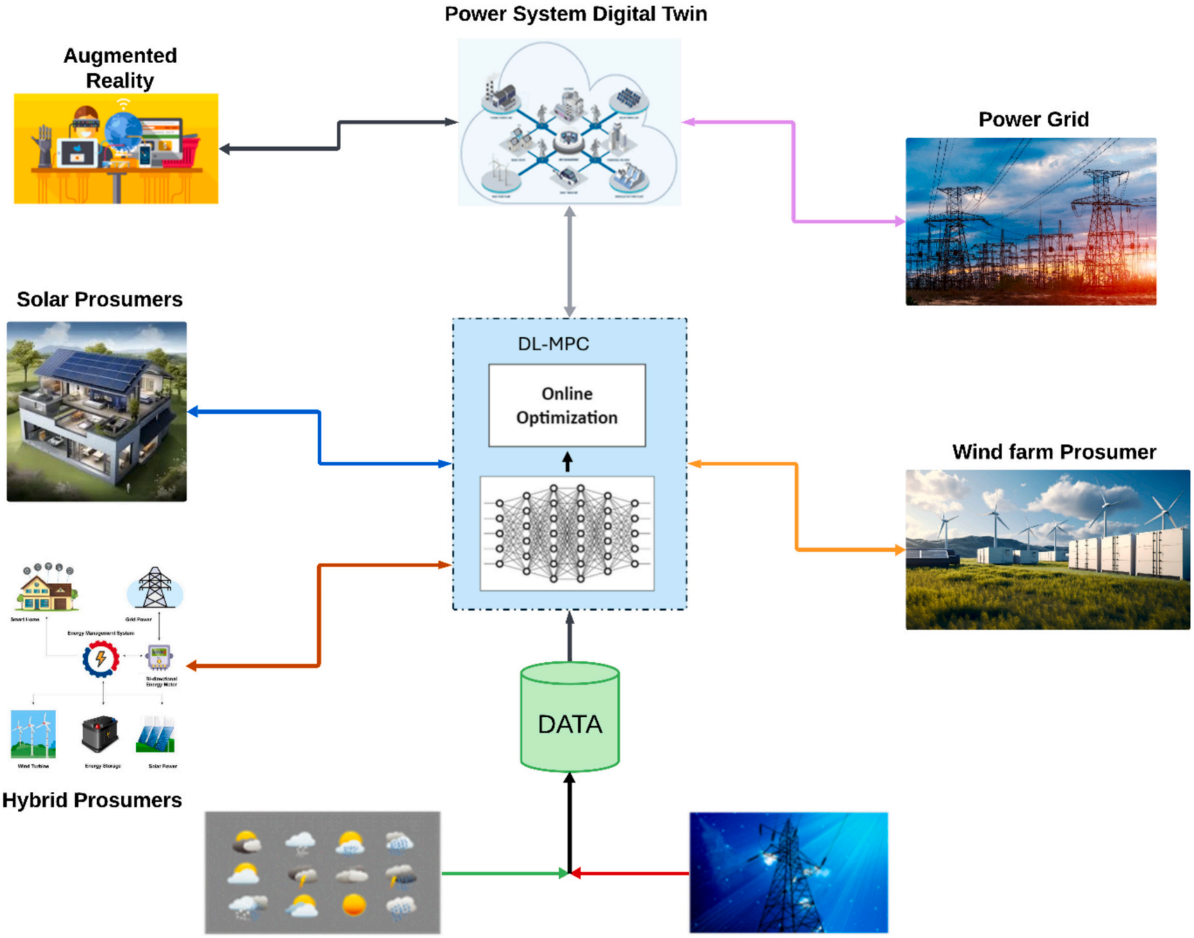


Fig. 1. DT model for DL-MPC-based Battery and storage optimisation.

of information, including the forecasts of weather (solar irradiance, wind speeds, temperature), trends around energy use at specific times of the year, time of day factors, and user behavior patterns. This extensive data enables the deep learning model to provide accurate predictions for energy generation and consumption for the upcoming hours, subsequently relayed to the MPC framework to facilitate the decision-making process. The best advantage of the DL model is that it can learn and adapt to new data. As it gathers more information, the model self-trains on new batches of data, increasing predictive accuracy. This guarantees that the system will work overtime, as the system can adjust to changing conditions over time, which corresponds well with the characteristics of renewable energy systems in prosumer districts, including high variability.

3.3. *Model predictive control for battery and storage optimization*

MPC is the underlying decision-making framework to control energy storage and distribution optimally. At every time step, the MPC formulates an optimization problem leveraging the predictions of the DL model to establish the optimal actions in terms of charging/discharging of the battery and the energy exchange between the prosumer network and the grid. MPC works by evaluating a finite time horizon in the future and calculating control inputs that maximise system efficiency, subject to operational constraints. These limitations include battery storage capacity, energy demand thresholds, grid interaction ranges, and system stability constraints. The idea is to store energy during peak periods of renewable generation and release it at high-demand times, limiting the need for a grid and reducing operational costs.

MPC helps optimize the battery and storage so that the charging/discharging cycles of the battery are efficiently used while minimizing the use of renewable resources, thus increasing cost efficiency and battery life. As such, the MPC framework may ask for charging the battery when solar is abundant in the grid and discharging when the grid is more expensive. Not only will this create a great deal of money savings, but it will also create energy savings and reduce the need for fossil fuel-generated electrical use, reducing its environmental impact. Further, the MPC framework continually learns from interacting with the Digital Twin, enabling real-time adaptation of the control strategy to changing conditions. The closed-loop control system enables a high degree of adaptability, allowing the system to respond in real time to changes in generation and demand.

3.4. *Augmented reality interface for enhanced user interaction*

We have enhanced user interaction and offered more insights into the energy management process by integrating an AR interface. With the AR interface, you access a real-time AR visualization of energy flows in the prosumer district with insights on energy generation, battery storage levels, and consumption trends. This allows prosumers and system operators to intuitively and quickly interact with the DT through AR [24,25]. The dashboard presents crucial data, including real-time energy consumption, estimated energy demand, renewable energy production patterns, and battery performance visually. Tangible visualization, for instance, allows users to be presented with a 3D rendering of the prosumer network along with live updates about solar panel output, battery charge levels, and energy flows between the grid and the prosumer system.

AR enables customers to understand their energy consumption and make better choices related to energy. For example, prosumers can use this information to visualise when it is most cost-effective to consume stored energy and when it would be advantageous to send surplus energy back into the grid. Interaction on this scale enables users to exercise greater control over their energy consumption, encouraging a more participative and informed approach to energy management. Moreover, in addition to the data itself, system operators may navigate the AR interface, displaying all the energy system performance data in real time and optimizing energy storage and distribution at the point.

3.5. *Energy flow and control process in prosumers districts*

The energy flow process through a renewable energy prosumer district is dynamic; respective stages are interconnected, from data collection and forecasting to optimisation and control. The system collects real-time data from the prosumer network, including energy generation from renewable sources, charge/discharge cycles of batteries, and energy consumption at the district level. The DT calculations process this data and update a virtual network model. Then, the DL model predicts future energy demand and supply based on weather and end-user information. The MPC framework utilises these predictions and computes the optimal control strategy for engineered energy flows between the prosumer network set and the grid. For example, the MPC framework decides when to charge/discharge the battery, how much energy to export from the grid, and how to satisfy demand cost-effectively by managing energy flows. The system is continuously tuned with the Digital Twin, adjusting the control actions based on real-time feedback to manage the energy even when the conditions change.

3.6. *Optimization criteria and sustainability objectives*

The optimization process is subject to several key criteria addressing economic efficiency and sustainability goals. The focus is on optimizing the usage of renewable energy to ensure energy comes from on-site generation, not the grid. To do this, we optimize batteries' charging and discharging cycles to store excess renewable energy and use it when there is a high demand. Besides maximizing the use of renewable energy sources, the system also aims at minimizing operating costs. These may include lowering grid electricity costs, optimizing battery performance to reduce maintenance costs, and prolonging the battery's life cycle with optimal charge/discharge cycles. In addition, the system encourages sustainability through energy waste reduction, lowering dependence on non-renewable energy sources, and helping signatory parties achieve environmental goals. DL, MPC, DT, and AR technologies are integrated into the architecture, allowing for efficient, sustainable, and highly adaptive energy storage and distribution management, particularly in renewable energy prosumer districts.

4. DT model design and analysis: DL with MPC optimization for battery storage

The formulation of DL-MPC is explained below:

4.1. *Problem setup*

We consider the IEEE 30-Bus System with three types of prosumers: solar, wind, and hybrid. Each prosumer $i \in N$ generates renewable energy $P_{G,i}(t)$, consumes energy $P_{load,i}(t)$, and manages battery storage $SOC_i(t)$.

4.2. *System dynamics and constraints*

The system is governed by energy balance, battery dynamics, and operational constraints, ensuring physical feasibility and stability. Energy Balance:

For each prosumer i, the energy balance at any time t is given by:

$$P_{G,i}(t) + P_{grid,i}(t) + P_{B,i}(t) = P_{load,i}(t) \quad \forall i, t \tag{1}$$

Where $P_{G,i}(t)$: Power generated by prosumer i at time t, $P_{grid,i}(t)$: Power exchanged with the grid at time t (positive for import, negative for export), $P_{load,i}(t)$: Load (consumption) of prosumer i at time t, and $P_{B,i}(t)$ Power stored in or discharged from the battery (positive for charging, negative for discharging).

Battery Dynamics: The state of charge (SOC) is updated based on battery charging and discharging:

$$\begin{aligned} SOC_i(t+1) &= SOC_i(t) + \eta_{ch,i} P_{B,i}(t), \quad \text{if } P_{B,i}(t) > 0 \quad \text{(charging)} \\ SOC_i(t+1) &= SOC_i(t) - \frac{P_{B,i}(t)}{\eta_{dis,i}}, \quad \text{if } P_{B,i}(t) < 0 \quad \text{(discharging)} \end{aligned} \tag{2}$$

Where, $SOC_i(t)$: State of Charge (SOC) of the battery at time t. $\eta_{ch,i}$ and $\eta_{dis,i}$ are the charging and discharging efficiencies, respectively.

SOC Limits: The state of charge of the battery must remain within specified limits:

$$SOC_{min,i} \le SOC_i(t) \le SOC_{max,i} \quad \forall i, t \tag{3}$$

Grid Interaction Constraints: The power exchange with the grid is subject to limits:

$$P_{grid,min,i} \le P_{grid,i}(t) \le P_{grid,max,i} \quad \forall i, t \tag{4}$$

Generation Limits: Each prosumer type has limits on renewable generation:

Solar Prosumer:

$$0 \le P_{G,i}^{solar}(t) \le P_{max,i}^{solar} \quad \forall i \in N_{solar}, t \tag{5}$$

Wind Prosumer:

$$0 \le P_{G,i}^{wind}(t) \le P_{max,i}^{wind} \quad \forall i \in N_{wind}, t \tag{6}$$

Hybrid Prosumer (solar + wind):

$$0 \le P_{G,i}^{hybrid}(t) \le P_{max,i}^{hybrid} \quad \forall i \in N_{hybrid}, t \tag{7}$$

4.3. Optimization objectives and power flow

The DL-MPC framework optimizes a multi-objective function, balancing operational costs, renewable energy utilization, and transmission losses, subject to power flow constraints.

Power Flow Equations: The standard AC power flow equations govern the power flow across the IEEE 30-Bus system:

$$\begin{aligned} P_i &= \sum_{j \in N} |V_i||V_j| \left(G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j) \right) \\ Q_i &= \sum_{j \in N} |V_i||V_j| \left(G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j) \right) \end{aligned} \tag{8}$$

where V_i and θ_i are the voltage magnitude and angle at bus i, and G_{ij} and B_{ij} are the conductance and susceptance between buses i and j.

Minimizing Operational Costs: The cost of importing energy from the grid and battery operation is minimized.

$$J_1(\mathrm{t}) = \sum_{t=1}^{T} \sum_{i=1}^{N} \left(c_{grid} P_{grid,i}(t) + c_{battery} \left(P_{B,i}(t) \right)^2 \right) \tag{9}$$

Where c_{grid} and $c_{battery}$ are the regulation weights for grid power and battery, respectively.

Maximizing Renewable Energy Utilization: We aim to maximise renewable energy generation and utilization:

$$J_2(\mathrm{t}) = -\sum_{t=1}^{T} \sum_{i=1}^{N} P_{G,i}(t) \tag{10}$$

Minimizing Transmission Losses: To improve grid stability, we minimize transmission losses:

$$J_3(\mathrm{t}) = \sum_{t=1}^{T} P_{loss}(t) \tag{11}$$

Overall Optimization Problem: The overall objective is to minimize the weighted sum of the cost, renewable energy utilization, and transmission losses:

$$\min_{P_G, P_{grid}, P_B, SOC} J(t) = \alpha_1 J_1(\mathrm{t}) + \alpha_2 J_2(t) + \alpha_3 J_3(t) \tag{12}$$

subject to all the constraints presented earlier.

Deep Learning-Based Forecasting Model: The DL model provides forecasts for generation and consumption:

$$\begin{aligned} P_{G,i}(t+1) &= f_{DL}\left(P_{G,i}(t), \text{Weather Data}, \text{Historical Data}\right) \\ P_{load,i}(t+1) &= g_{DL}\left(P_{load,i}(t), \text{Historical Data}\right) \end{aligned} \tag{13}$$

4.4. MPC formulation and algorithm

The optimization problem of the DL-MPC framework is presented as:

$$\min_{P_G, P_{grid}, P_B, SOC} J(t) = \alpha_1 J_1(\mathrm{t}) + \alpha_2 J_2(t) + \alpha_3 J_3(t) \tag{14}$$

Subject to

$$P_{G,i}(t) + P_{grid,i}(t) + P_{B,i}(t) = P_{load,i}(t) \quad \forall i, t$$

$$SOC_i(t+1) = \begin{cases} SOC_i(t) + \eta_{ch,i} P_{B,i}(t), & \text{if } P_{B,i}(t) > 0 \quad \text{(charging)} \\ SOC_i(t) - \dfrac{P_{B,i}(t)}{\eta_{dis,i}}, & \text{if } P_{B,i}(t) < 0 \quad \text{(discharging)} \end{cases}$$

$$SOC_{min,i} \le SOC_i(t) \le SOC_{max,i} \quad \forall i, t$$

$$P_{grid,min,i} \le P_{grid,i}(t) \le P_{grid,max,i} \quad \forall i, t$$

$$0 \le P_{G,i}^{solar}(t) \le P_{max,i}^{solar} \quad \forall i \in N_{solar}, t$$

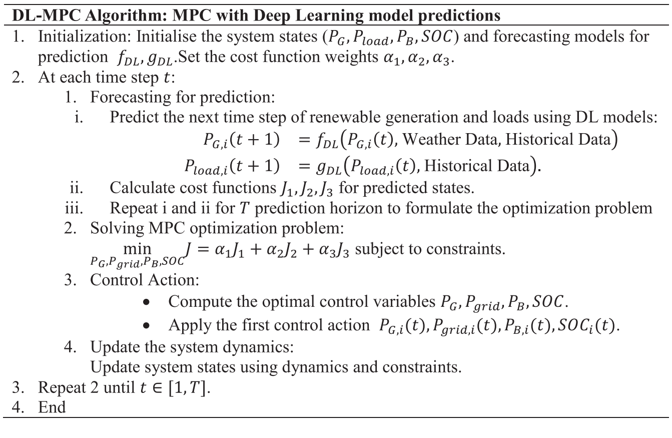
$$0 \le P_{G,i}^{wind}(t) \le P_{max,i}^{wind} \quad \forall i \in N_{wind}, t$$

$$0 \le P_{G,i}^{hybrid}(t) \le P_{max,i}^{hybrid} \quad \forall i \in N_{hybrid}, t$$

$$\begin{aligned} P_i(t) &= \sum_{j \in N} |V_i(t)||V_j(t)| \left(G_{ij} \cos(\theta_i(\mathrm{t}) - \theta_j(t)) + B_{ij} \sin(\theta_i(\mathrm{t}) - \theta_j(t)) \right) \\ Q_i(t) &= \sum_{j \in N} |V_i(t)||V_j(t)| \left(G_{ij} \sin(\theta_i(\mathrm{t}) - \theta_j(t)) - B_{ij} \cos(\theta_i(\mathrm{t}) - \theta_j(t)) \right) \end{aligned}$$

$$\begin{aligned} P_{G,i}(t+1) &= f_{DL}\left(P_{G,i}(t), \text{Weather Data}, \text{Historical Data}\right) \\ P_{load,i}(t+1) &= g_{DL}\left(P_{load,i}(t), \text{Historical Data}\right). \end{aligned}$$

The DL-MPC optimization problem is solved at each step to optimize the system's operational cost, renewable energy utilization, and transmission losses using DL predictions. The MPC algorithm is presented below:



DL-MPC Algorithm: MPC with Deep Learning model predictions

```
1. Initialization: Initialise the system states ($P_G, P_{load}, P_B, SOC$) and forecasting models for
   prediction $f_{DL}, g_{DL}$.Set the cost function weights $\alpha_1, \alpha_2, \alpha_3$.
2. At each time step $t$:
     1. Forecasting for prediction:
          i.   Predict the next time step of renewable generation and loads using DL models:
                   $P_{G,i}(t+1) = f_{DL}(P_{G,i}(t), \text{Weather Data, Historical Data})$
                   $P_{load,i}(t+1) = g_{DL}(P_{load,i}(t), \text{Historical Data})$.
          ii.  Calculate cost functions $J_1, J_2, J_3$ for predicted states.
          iii. Repeat i and ii for $T$ prediction horizon to formulate the optimization problem
     2. Solving MPC optimization problem:
          $\min_{P_G, P_{grid}, P_B, SOC} J = \alpha_1 J_1 + \alpha_2 J_2 + \alpha_3 J_3$ subject to constraints.
     3. Control Action:
          • Compute the optimal control variables $P_G, P_{grid}, P_B, SOC$.
          • Apply the first control action $P_{G,i}(t), P_{grid,i}(t), P_{B,i}(t), SOC_i(t)$.
     4. Update the system dynamics:
        Update system states using dynamics and constraints.
3. Repeat 2 until $t \in [1, T]$.
4. End
```

4.5. Convergence proof

The convergence of the DL-MPC is analyzed based on the boundedness of DL prediction errors, the optimization problem's feasibility, and the closed-loop system's stability.

Lemma 1. *Boundedness of DL Prediction Errors*.

The prediction errors of deep learning (DL) models for renewable generation and load are bounded.

Let the error between the true and predicted values of renewable generation and load is calculated as:

$$\epsilon_P(t) = \left|P_{G,i}^{true}(t) - P_{G,i}^{pred}(t)\right|, \epsilon_{load}(t) = \left|P_{load,i}^{true}(t) - P_{load,i}^{pred}(t)\right|.$$

For bounded error, assuming that the DL models are trained with sufficient data and prediction errors satisfy the following: $\epsilon_P(t) < \epsilon_{\max}$ and $\epsilon_{load}(t) < \delta_{max}$. The bounded error ensures that the prediction using the DL model for optimization of MPC control is close to the actual dynamic behavior of the system.

Lemma 2. *Convexity of MPC Problem*.

The MPC optimisation problem is convex to control variables $\mathrm{P}_{\mathrm{grid}}$, P_{B}, $\mathrm{P}_{\mathrm{load}}$, and SOC.

The convexity of the optimization problem is analyzed using the objective function and constraints of the DL-MPC formulation.

1. Objective function:

The objective function is a weighted sum of three cost functions. If all three functions are convex, their weighted sum is also convex.

The operational cost function $J_1 = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(c_{grid}P_{grid,i}(t) + c_{battery}\left(P_{B,i}(t)\right)^2\right)$, consists of a linear term $c_{grid}P_{grid,i}(t)$and $c_{battery}\left(P_{B,i}(t)\right)^2$ a quadratic term. $J_1$is a quadratic positive semidefinite function; hence, it is a convex function. The renewable utilization cost function J_2 is a linear function. The transmission loss term J_3 is calculated using a quadratic power flow equation; hence, it is a convex function. Therefore, the objective function in the DL-MPC optimisation function is a convex function.

2. Constraints:

The energy balance equation, SOC limits, and power generation limits are linear, and the dynamics are piecewise linear. The power flow equations are linear, so constraints also satisfy convexity with modification of the battery dynamics.

Hence, the optimization formulation is a convex problem.

Theorem: Stability and Convergence of DL-MPC.

The DL-algorithm converges to a globally optimal solution as $T \rightarrow \infty$, provided that the optimization formulation is convex and bounded DL models' prediction error.

Proof: The proof consists of the following steps: optimality, recursive feasibility, DL model bounded error predictions and stability of the closed-loop system.

1. Optimal at each time step t:

The DL-MPC at each time step t solves a convex optimization problem over a finite horizon N. The convexity of the optimization problem guarantees an optimal solution for the control variables at each time step t using Lamma 2.

2. Recursive Feasibility of the Optimization Problem:

The recursive feasibility of the optimization problem ensures that the solution at time step t is feasible, and then it is also feasible in future time step $t+1$. The state variables remain within the admissible set over time.

The state transition $SOC_i(t) \in \left[SOC_{min,i} \;\; SOC_{max,i}\right]$ than $P_{B,i}(t) \in \left[-\frac{\eta_{dis,i}\left(SOC_i(t) - SOC_{min,i}\right)}{\Delta t} \quad -\frac{\left(SOC_{max,i} - SOC_i(t)\right)}{\eta_{ch,i}\Delta t}\right]$.

The $SOC_i(t+1)$ will remain feasible at the next time step.

Similarly, the energy balance equation and generation constraints satisfy as we have bounded prediction errors, as proved in Lemma 1. This implies that.

$\epsilon_P(t) = \left|P_{G,i}^{true}(t) - P_{G,i}^{pred}(t)\right| < \epsilon_{max}, \;\; \epsilon_{load}(t) = \left|P_{load,i}^{true}(t) - P_{load,i}^{pred}(t)\right| < \delta_{max}$.

3. Closed-loop System stability:

The closed-loop stability is demonstrated by showing that the DL-MPC cost function is a Lyapunov function that decreases over time.

The DL-MPC objective function is given by:

$$J^*(t) = \min_{P_G, P_{grid}, P_B, SOC} J(t) = \min_{P_G, P_{grid}, P_B, SOC} \sum_{t=1}^{T} \left(\alpha_1 J_1(t) + \alpha_2 J_2(t) + \alpha_3 J_3(t)\right)$$

At time step t, the cost function $J^*(t)$ satisfies: $J^*(t+1) \leq J^*(t) - \Delta J(t), \Delta J(t) > 0$.

The receding horizon strategy of the DL-MPC ensures that $J^*(t+1) \leq J^*(t)$ and the system converges to the steady-state solution. At $t \rightarrow \infty$, $J^*(t) \rightarrow J_{steady-state}$ corresponding to the globally optimal solution of the infinite-horizon problem.

4.6. Detailed Deep Learning model architecture and training

The DL model employed in the proposed DL-MPC framework integrates CNNs and LSTM networks to forecast energy generation and consumption in the prosumer network. Below, we describe the architecture, training process, and dataset details.

4.6.1. CNN-LSTM model architecture

The DL model is a hybrid CNN-LSTM architecture that captures spatial and temporal energy data dependencies. The architecture consists of the following layers:

- Input Layer: Accepts multivariate time-series data with features including solar irradiance (W/m^2), wind speed (m/s), temperature (°C), humidity (%), cloud cover (%), historical energy generation (kW), load demand (kW), and battery state of charge (SOC, %). The input shape is ((T, F)), where $T = 24$ (hourly data over a 24-hour window) and F = 8 (number of features).
- CNN Layers: Two 1D convolutional layers extract spatial features from the time-series data. The first layer has 64 filters with a kernel size of 3 and ReLU activation, followed by a max-pooling layer (pool size = 2). The second layer has 32 filters with the same kernel size and activation, followed by another max-pooling layer. These layers reduce dimensionality while capturing local patterns, such as weather variables and energy generation correlations.
- LSTM Layers: Two LSTM layers model temporal dependencies. The first LSTM layer has 100 units, and the second has 50 units, with tanh activation and return_sequences = True for the first layer to pass sequences to the next. A dropout layer (rate = 0.2) is applied after each LSTM layer to prevent overfitting.
- Dense Layers: A fully connected layer with 50 neurons and ReLU activation processes the LSTM output, followed by an output layer with 2 neurons (linear activation) to predict energy generation and load demand for the next time step.
- Total Parameters: Approximately 150,000 trainable parameters, optimized using the Adam optimizer with a learning rate of 0.001.

4.6.2. Training dataset

The DL model is trained on a synthetic dataset inspired by real-world energy systems, comprising 100,000 samples (approximately 2GB). The dataset includes:

- Weather Data: Solar irradiance (0–1000 W/m^2), wind speed (0–15 m/s), temperature (2.93–46.10 °C), humidity (30–90 %), and cloud cover (0–100 %), sourced from the National Renewable Energy Laboratory (NREL) and NASA POWER Project.
- Energy Data: Energy generation (0–100 kW), load demand (0–10 kW), battery SOC (0–20 %), and grid import/export (0–100 kW), derived from SCADA systems, smart meters, and battery management systems (BMS).
- Temporal Resolution: Hourly data captures diurnal and seasonal variations over one year.
- Data Preprocessing: Features are normalized to [0,1] using min-max scaling. The dataset is split into 70 % training, 15 % validation, and 15 % testing. A sliding window approach (window size = 24 h) creates input-output pairs for supervised learning.

4.6.3. Training process

The model is trained for 100 epochs with a batch size of 64, using Mean Squared Error (MSE) as the loss function. Early stopping is applied if validation loss does not improve for 10 epochs, with the best model saved based on validation loss. The training process leverages a GPU (NVIDIA Tesla V100) to handle the computational load, achieving convergence within 2 h. The final model achieves an MSE of 0.002 on the test set, indicating high predictive accuracy.

4.7. Detailed MPC algorithm specification

Based on DL predictions, the MPC algorithm optimizes battery charging/discharging and grid interactions. Below, we elaborate on its formulation, solver, and implementation details.

4.7.1. MPC formulation

The MPC solves an optimization problem at each time step (t), over a prediction horizon $N = 24$ N = 24 h, to minimize the objective function defined in (12): $J(t) = \alpha_1 J_1(\mathrm{t}) + \alpha_2 J_2(\mathrm{t}) + \alpha_3 J_3(t)$.

where: J_1 is operational cost, including grid import costs and battery degradation costs, J_2 is penalty for underutilization of renewable energy, J_3 is transmission losses in the IEEE 30-Bus system, weights $\alpha_1 = 0.5$, $\alpha_2 = 0.3$, and $\alpha_3 = 0.2$ are tuned empirically to balance cost, renewable utilization and grid stability.

The optimization is subject to constraints (Section 4.2) from Eqs. (1) to (8) that include Energy balance, Battery dynamics, power grid interaction limits, and generation limits based on prosumer type (solar, wind, hybrid).

4.7.2. Solver and implementation

The MPC optimization problem is convex (as proven in Section 4.5) and solved using the CVXPY library in Python, with the ECOS solver for quadratic programming. The solver computes optimal control actions every hour, applying the first control action and shifting the horizon forward (receding horizon strategy). The average computation time per step is 0.5 s on a standard CPU (Intel Xeon, 2.4 GHz), ensuring real-time applicability.

4.7.3. Integration with DL predictions

The DL model provides forecasts for generation and consumption from (13) for prediction horizon, which are fed into the MPC to formulate the optimization problem. The boundedness of DL prediction errors (Lemma 1, Section 4.5) ensures that MPC decisions remain robust despite forecasting uncertainties.

5. Performance validations

5.1. Simulation settings

This section describes how to establish an analogous environment in Python for a Deep Learning-based Digital Twin with an Augmented Reality (DL-DT-AR) framework intended for MPC in a renewable energy prosumer district: for that, we will include 100,000 samples in their synthetic dataset. This will involve simulating time-series data points that represent relevant time-series metrics needed for prosumer energy, such as energy generation from solar or wind, consumption, battery state-of-charge SOC, grid consumption, and grid delivery. Due to the dynamic and changing nature of factors such as renewable generation variability, demand profiles, and weather conditions (solar irradiance, temperature, and wind speed), the dataset (approximately 2GB) will include a combination of these variables. The dataset structure is inspired by data sources covered by some real-life setups as follows:

(a) Weather Data: Solar irradiance, temperature, wind speed, humidity, clouds, etc., real-time data is sourced from the National Renewable Energy Laboratory (NREL) for solar and wind data; NASA POWER Project for global solar and meteorological data; APIs such as Weather Underground or OpenWeather for real-time, localized weather conditions.

(b) Energy Generation Data: These are real-time production metrics from renewable assets such as solar panels and wind turbines that can typically be monitored via SCADA Systems (Supervisory Control and Data Acquisition), Energy Management Systems (EMS) that can capture generation metrics at a very granular level as well as IoT-enabled sensors that connect directly to these renewable energy assets.

(c) Consumption Pattern: The real-time energy consumption data provides prosumers' utilization patterns, including commercial and residential consumption. Sources included Smart Meter Data for granular tracking (generally supplied in conjunction with your utility companies), Building Management Systems (BMS) for commercial sites, IoT devices, or Home Energy Management Systems (HEMS) for insights into residential consumption.

(d) Battery SOC and Health status: Data related to battery SOC, charge/discharge cycles, and general health status, commonly regulated by BMS, having SOC-estimation and health-monitoring functions, and Smart Inverters governing storage status and grid interaction.

(e) Grid Interaction & Price Signals: Power import/export levels and real-time demand response signals, including real-time electricity prices, from Smart Grid Infrastructure (such as Advanced Metering Infrastructure, AMI) and Utility APIs (real-time electricity price, demand response notifications).

(f) Historical Data Archives (for model training): Historical data archives provide historical datasets used for model training, which track trends in weather, energy generation, and demand variations over time. Ranging from the NREL Open Data Platform to EIA datasets to local utility archives and smart meter repositories.

In this DT context, the DL model will use the dataset to predict future energy demand and generation. The MPC will then utilize these insights to optimize battery storage and grid interactions as conditions change. Like traditional RL-based control strategies, this DL-MPC-based framework is reinforced by the AR component to visualise real-time energy statistics for intuitive user interaction and decision-making process, resulting in increased energy efficiency and cost-saving for each prosumer or the entire prosumer district.

5.2. Performance metrics

This study integrates the DL-MPC, DT, and AR approaches to optimize battery and storage systems within renewable energy prosumer districts. The achieved simulation results reported in Figs. 2 to 23 and Tables 1 to 4 reveal a new dynamic architecture that allows flexibility based on energy demand and renewables generation and storage needs.

5.2.1. DL-MPC algorithm convergence

The convergence of the DL-MPC algorithm is shown in Fig. 2. The prediction error is reduced over successive iterations. The x-axis represents the iteration count, and the y-axis represents the prediction error value. An exponential decline in the curve indicates the rapid improvement in DL-MPC to identify the optimal control actions. The solution converges to a near-optimal solution as iteration progresses, the error curve flattens, and improvement becomes smaller. The prediction error convergence in the finite step indicates that DL-MPC efficiently achieves stable and consistent optimization, which is important for real-time control action in renewable energy prosumer networks.

5.2.2. Predictive Accuracy of DL-MPC

The predictive accuracy of DL-MPC is compared with conventional MPC, and results are shown in Fig. 3. The DL-MPC high-level pattern recognition capabilities achieved superior predictive accuracy compared to conventional MPC. The x-axis represents time, and the y-axis indicates the energy values. There are three curves: baseline MPC (conventional MPC), DL-MPC (using CNN deep learning model), and DL-MPC (using LSTM machine learning model) predictions. The two DL-MPC models' curves are closely aligned, while the baseline MPC deviates significantly. The improvement in the DL-MPC framework is due to the DL model's ability to capture nonlinear patterns in energy data and allow informed, optimized MPC control actions. Accurate energy generation and demand forecasts reduce operational errors and system reactions by preemptive storage decision-making instead of reactive correction.

5.2.3. Digital twin based real-time dynamic optimization

The real-time dynamic optimization of energy flows in the prosumer network is implemented using the DT model, and the results are depicted in Fig. 4. The x-axis represents the real-time, and the y-axis represents the energy flow based on battery SOC, power grid import or export energy. The figure illustrates that DT-based dynamic optimisation synchronises the real-world system data. The DT prediction refines the control actions to optimize energy storage, grid energy import, and renewable energy utilization for smooth energy flow.

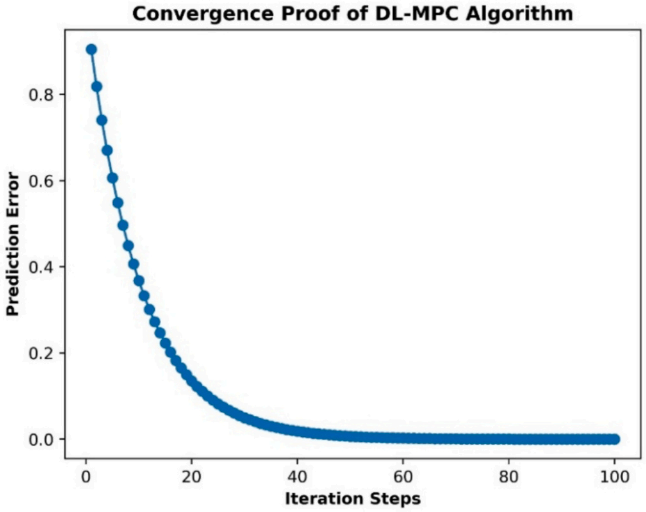


Fig. 2. DL-MPC Algorithm Convergence.

5.2.4. Adaptive energy storage management for prosumers

The adaptive energy storage management for prosumers controlled by the DL-MPC framework is compared with conventional MPC, as shown in Fig. 5. The x-axis represents time, and the y-axis tracks the percentage of the battery's SOC to depict the battery's charging and discharging behavior. Fig. 5 demonstrates a distinct time for battery charges during the availability of renewable energy and discharge during peak load demand. The DL-MPC enhances the storage use capability compared to the baseline model's control action in response to the dynamic variation of renewable energy generation and load demands. The DL-MPC adaptive energy storage management reduces grid reliance, extends battery life, and minimises energy costs.

5.2.5. Predictive maintenance with real-time anomaly detection

Fig. 6 presents a 3D surface plot highlighting the real-time anomaly identification in the battery and storage section of the system. The x-axis denotes time. The y-axis monitors operational system variables (such as SOC, voltage, or temperature), while the z-axis represents the anomaly score. The peak at the z-axis signifies the deviations from expected battery behavior and thus predicts the changes that lead to a failure or health issue of the system. The Digital Twin proactively identifies the anomaly and allows operators to intervene for predictive maintenance to avoid critical failure. This approach enhances system reliability, reduces downtime, and extends the battery lifetime. The predictive maintenance using anomalies over time is also visualized in Fig. 7 using a 3D heatmap. The maintenance score is calculated over time, the color intensity indicates the anomaly severity level to detect the patterns of anomalies. The heatmap pinpoints the time and component to support real-time monitoring and proactive maintenance.

5.2.6. Energy balance optimization

The energy balance optimization is presented in Fig. 8 using a 3D temporal energy balance in the prosumer network. The energy balance is visualized in days and hours to track the battery's usage, grid energy import, and energy export in response to the generation and load demand variation. The graph visualizes the temporal variation in energy balance influenced by the day and nighttime and fluctuation in generation and load demands.

5.2.7. Operation cost statistics

The optional cost optimization statistics are illustrated in Fig. 9, the bar plot compares the DL-MPC cost and baseline MPC design. The total operational cost is presented on the y-axis, while the x-axis identifies two models. The DL-MPC approach noticeably reduced 20 % operational cost, resulting in less reliance on the power grid, optimized battery usage, and improved energy flow control. The DL-MPC in the prosumer network promotes economic and sustainable energy flow solutions.

5.2.8. Real-time energy flow

Fig. 10 demonstrates the real-time energy flow within a prosumer network using a 3D plot, capturing the exchange between solar, wind, and battery storage. The renewable energy and load are represented using different markers presented on the plot, this visualization illustrates how the DL-MPC framework manages real-time energy flow. The framework based on the DL model manages real-time energy flows that ensure energy utilization and minimize import grid power to fulfil the prosumer energy needs.

The prosumer's grid dependency and self-sufficiency are depicted in Fig. 11 using a 3D plot. The plot shows an inverse relationship between grid dependency and self-sufficiency, as expected, with transition over time due to variations in renewable generation. The graphs help visualise the DL-MPC framework's efficiency in minimizing grid dependence and integration of renewables and storage systems. The load demand distribution across different prosumers in the network is depicted in

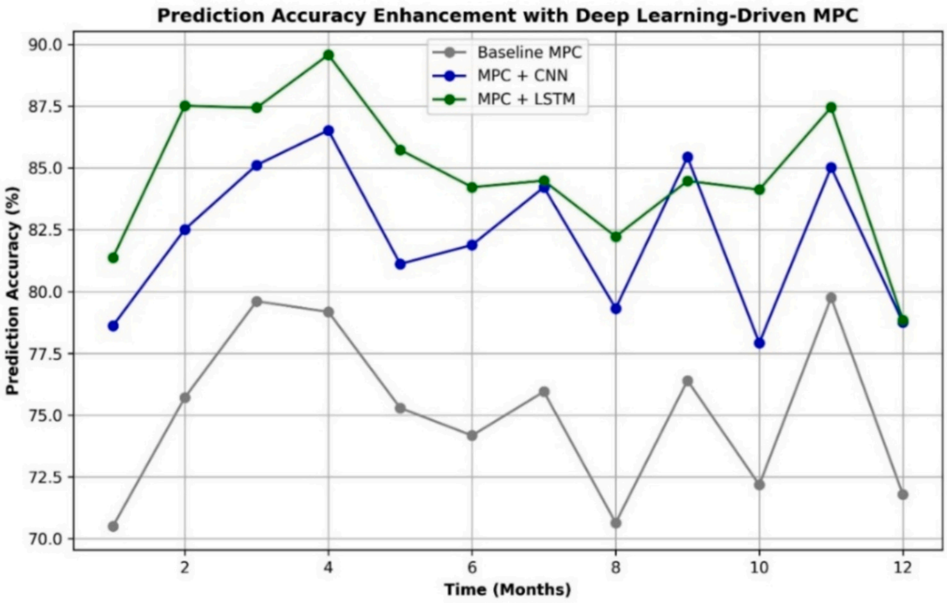


Fig. 3. Predictive Accuracy Enhancement with DL-MPC.

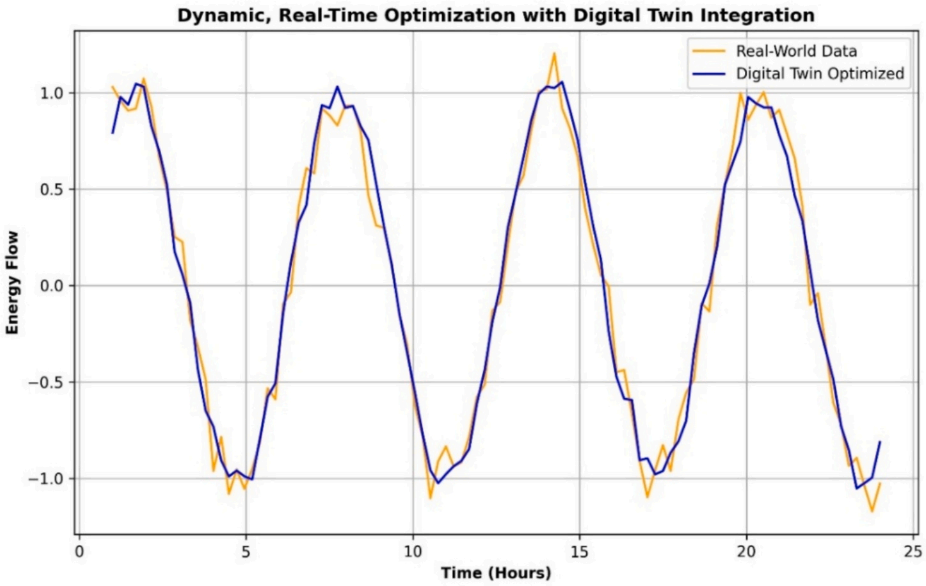


Fig. 4. DT-based real-time dynamic optimization.

Fig. 12 using a 3D plot. The plot demonstrates the load fluctuation across prosumers due to consumption variations.

5.2.9. *Network resilience model*

The network resilience is visualized in Fig. 13 using a 3D plot between time, percentage of stress level, and percentage of resilience under operational conditions. There is an inverse relationship between stress level and resilience in the system over time. The graph demonstrates that the DL-MPC reacts predictably to manage increasing stress over time.

5.2.10. *Energy generation predictions*

The DL-MPC performance for energy generation prediction is depicted in a 3D plot in Fig. 14 between generation, day, and time. The smooth surface indicates a stable forecast and a reduction in forecasting error. Based on an improved forecasting model prediction, the DL-MPC generates improved control decisions to manage battery storage, load demand, and grid interactions.

The renewable energy forecasting for solar and wind is shown in a 3D plot in Fig. 15. There are fluctuations in renewable generation, which indicate the efficiency of the DL model predictions. This accurate forecasting enables the DL-MPC to optimize the battery storage.

5.2.11. *SOC distribution and adaptive storage cycles*

The SOC distribution for multiple prosumers' battery storage 3D map between prosumer, load, and SOC is illustrated in Fig. 16. The DL-MPC ensures balanced battery storage utilization and maintains optimal SOC for each prosumer to prolong the battery life. The 3D plot visualizes charged and discharged batteries across the network, the z-axis level indicates the different battery usage or ideal.

Fig. 17 illustrates how battery storage switches between charging, discharging, or ideal states over time. The DL-MPC actively controls the

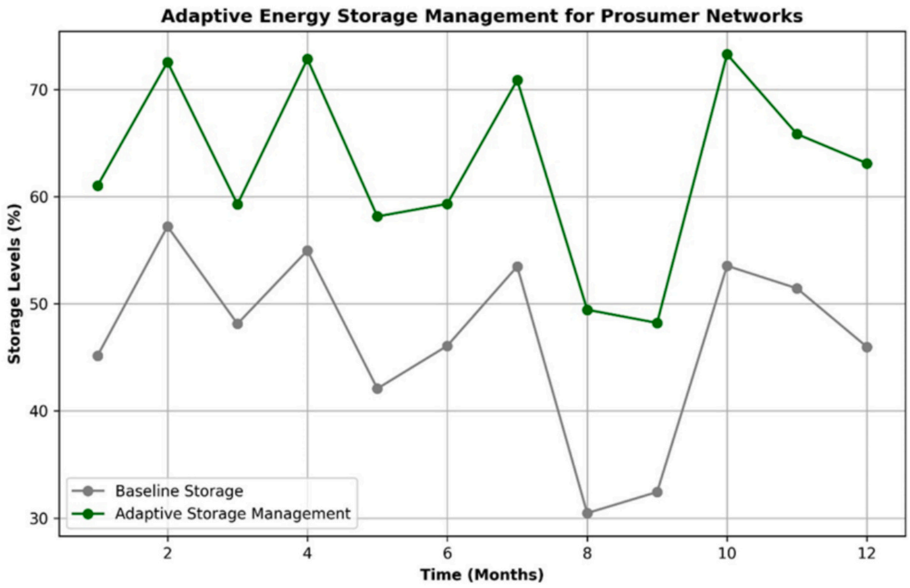


Fig. 5. Adaptive energy storage management for prosumers.

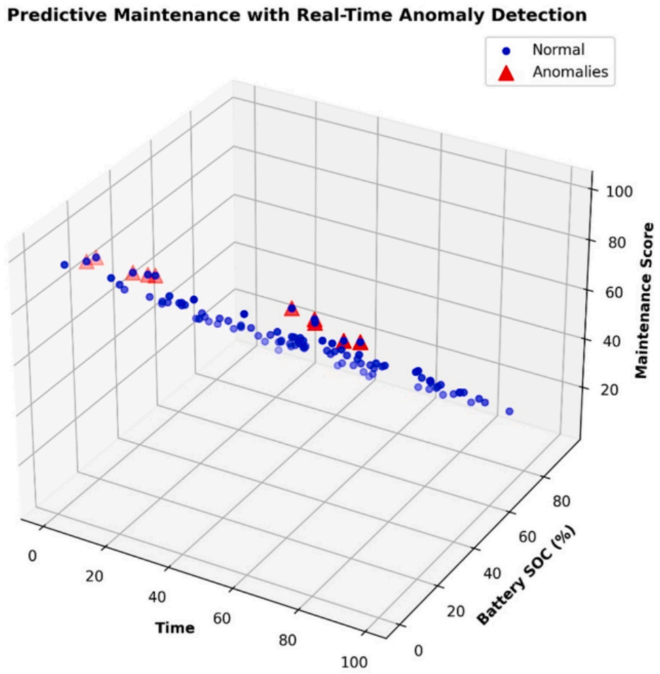


Fig. 6. 3D plot of predictive maintenance with real-time anomaly detection.

charging and discharging of the batteries over time to enhance battery utilization. This adaptive strategy enhances renewable energy utilization and provides economical energy cost over grid import.

5.2.12. *Environmental and cost analysis*

A comparative analysis of different power demands, efficiency, and operational costs to analyze the environmental effect of CO_2 emission is presented in Fig. 18. The cost savings and CO_2 reduction are directly proportional, and high demand for renewables' availability reduces carbon emission more than low generation or battery-only operations. The efficient management of battery storage using DL-MPC also reduces carbon emissions and highlights the economic and environmental benefits of the proposed framework.

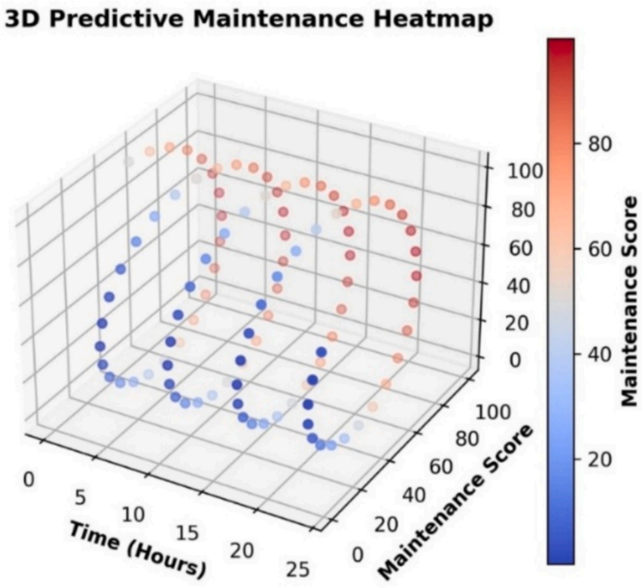


Fig. 7. 3D plot of predictive maintenance heatmap.

5.2.13. *Scalable solution for decentralized energy systems*

The scalability of a distributed energy system using DL-MPC is demonstrated in Fig. 19, which uses three prosumers with different consumption and storage patterns. The three prosumers are residential, commercial, and industrial. The plot shows that the DL-MPC system maintains efficiency and control performance in scalable prosumer networks. These results emphasise that the DL-MPC framework is adaptable, scalable, and suited for small and large decentralized prosumer grids.

5.2.14. *AR-based real-time energy flows and storage*

AR offers a dynamic, real-time window into the operational state of the energy system, as illustrated in Fig. 20. The visual shows current energy flows from solar and wind sources, battery levels, and grid dependency, providing a quick overview of the system's balance. The interface is designed for intuitive use, typically accessed via a smartphone or AR headset. Users can monitor live data such as output

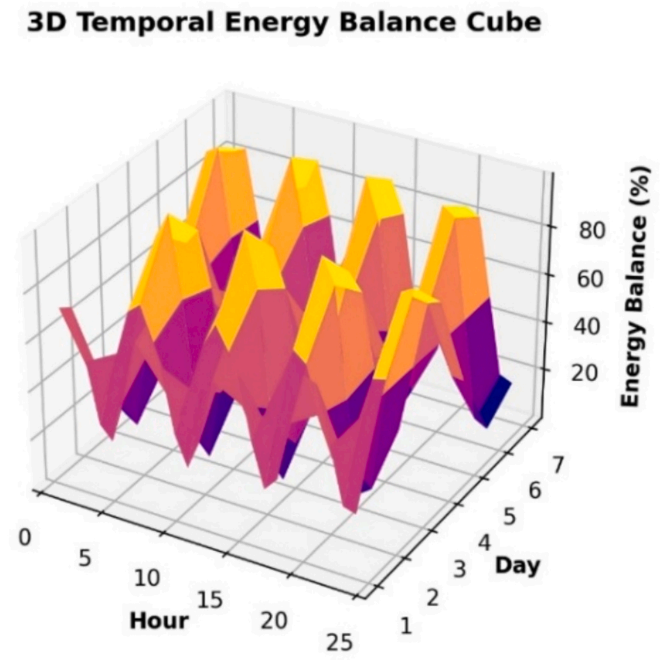


Fig. 8. 3D plot of energy balance optimization.

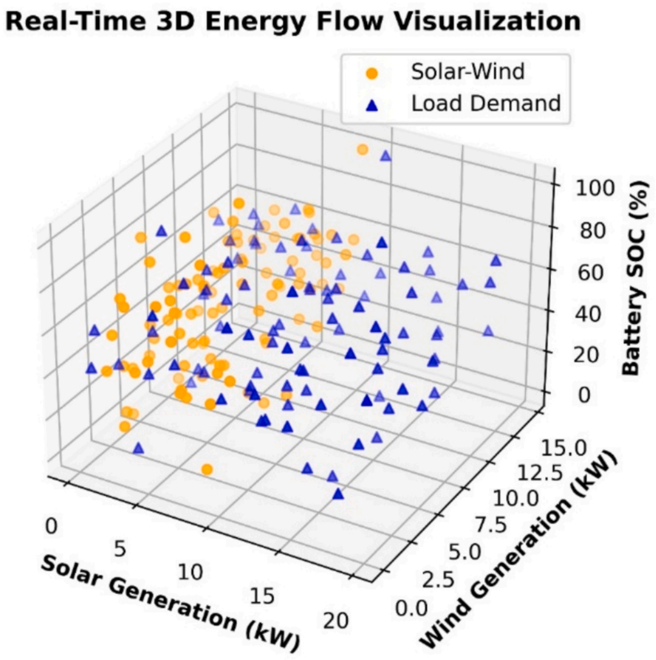


Fig. 10. 3D plot of real-time energy flow.

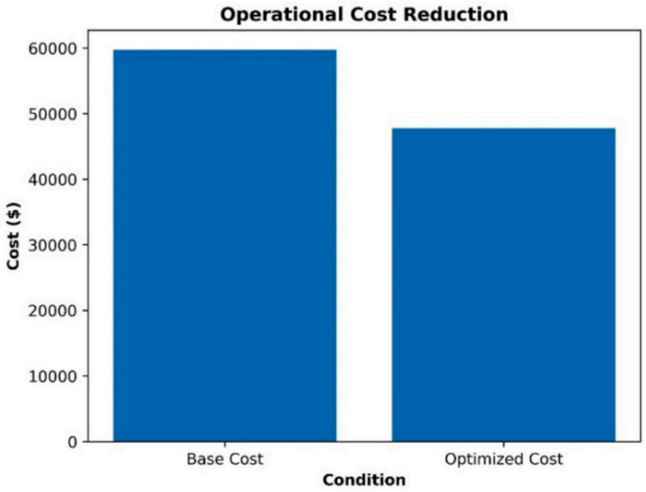


Fig. 9. Operation cost statistics.

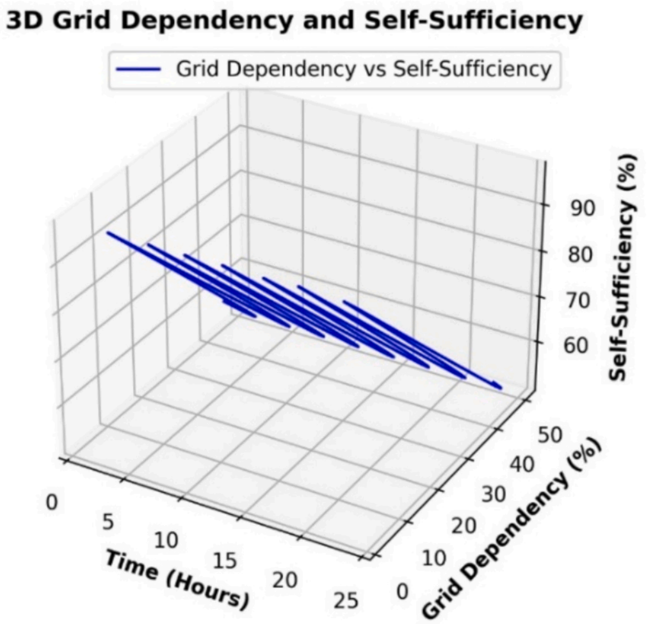


Fig. 11. 3D plot of grid dependency and self-sufficiency.

fluctuations or storage levels through visual overlays on physical components or system dashboards. Interactive features—like touch, gesture recognition, or voice commands—allow users to switch between data views, track historical performance, or initiate control actions directly within the interface.

This hands-on interaction improves user understanding of the system and encourages faster, more informed responses. For example, users can quickly assess battery reserves or grid reliance when renewable input drops and decide on corrective measures in real time. AR helps prosumers stay engaged and better manage their energy consumption and contributions by presenting critical information in a spatial and interactive format.

Fig. 21 presents the performance metric of Digital Twin combined with AR, which consists of the percentage improvement in predictive accuracy, real-time decision-making, dynamic control and adaptability, optimisation, scalability, cost reduction, and renewable utilization. The plot demonstrates an increase in all key performance metrics due to DT and AR integration for fast, data-driven decisions. The benefits of AR-DT integration are further highlighted in Fig. 22, including battery life extension, grid reliance reduction, carbon emission reduction, fast response time, and improved user engagement.

Based on a digital twin with AR, the DL-MPC enhances the system's overall performance, as depicted in Fig. 23. The DL-MPC framework improved performance compared to conventional MPC methods, showing improved energy efficiency, operation cost, battery optimisation, decision-making speed, renewable generation usage, and demand forecast. This figure summarizes the overall success of the framework and emphasizes the capability to deliver superior energy management performance in a smart prosumer grid.

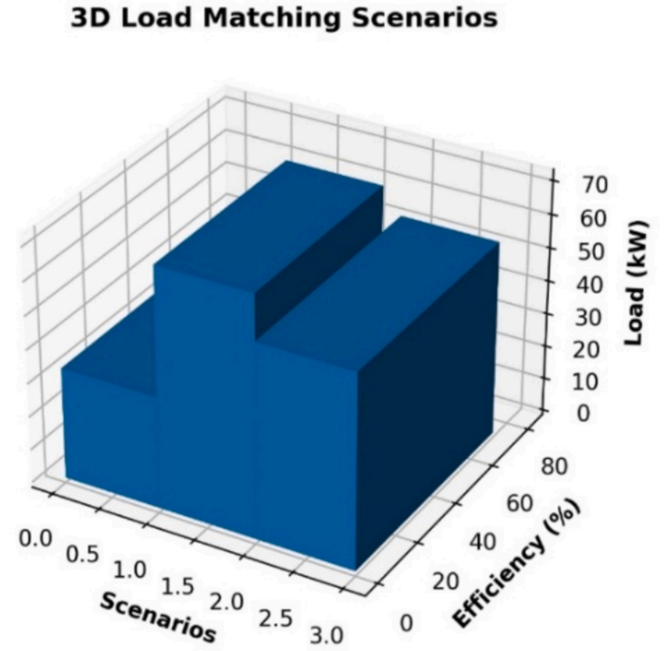


Fig. 12. 3D plot of load mapping.

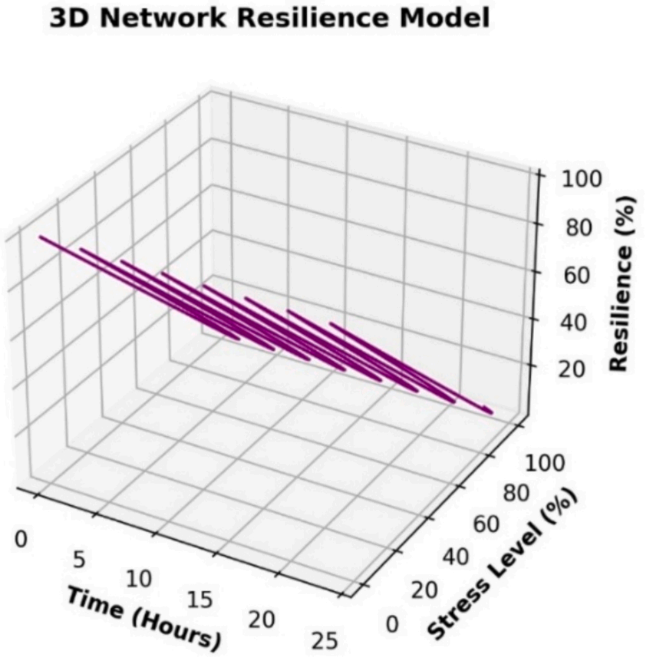


Fig. 13. 3D plot of network resilience model.

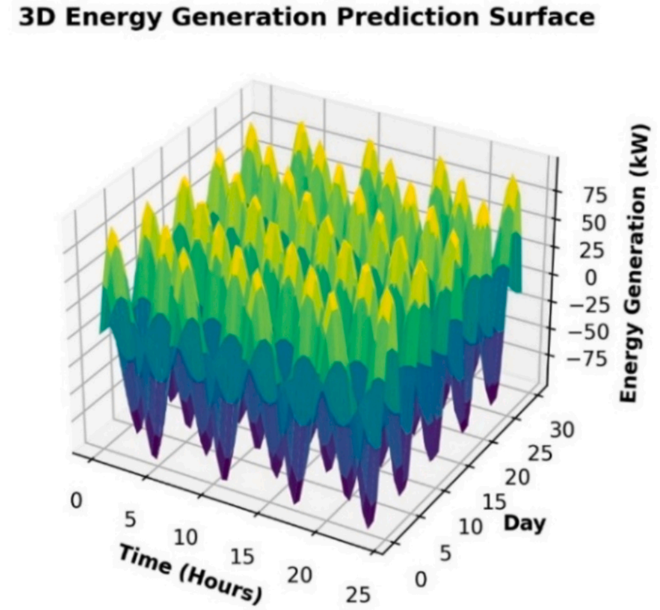


Fig. 14. 3D surface plot of energy generation prediction.

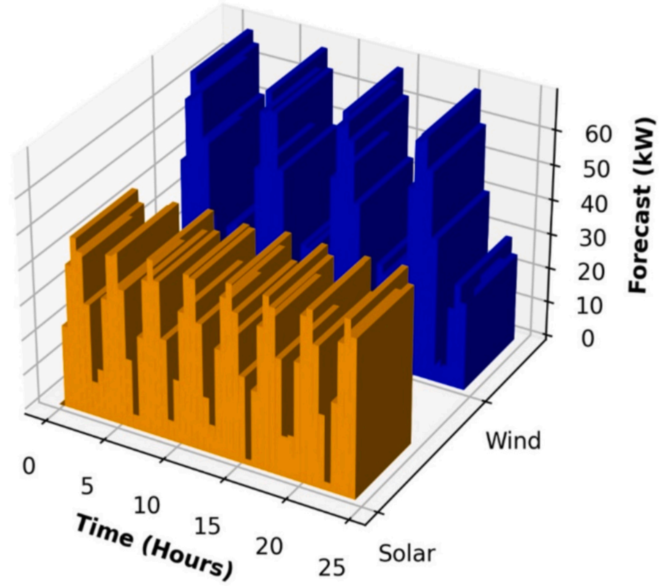


Fig. 15. 3D renewable energy forecasting.

5.2.15. *Tabular analysis of DL-MPC performance*

Table 1 compares operational costs and energy efficiency between a baseline model and the proposed DL-MPC framework. The table highlights the significant cost reduction and efficiency improvement achieved with the DL-MPC system. The operational cost for the base model is \$59,752.54, while the price is reduced to \$47,802.03 with the DL-MPC system, reflecting a 20 % reduction. Energy efficiency also increases from 37.37 % in the base model to 70 % in the DL-MPC framework, indicating better utilization of renewable energy and battery resources. This table demonstrates the superior performance of the DL-MPC system in managing battery storage, reducing reliance on the grid, and enhancing energy efficiency, making it a more cost-effective and sustainable solution for prosumer networks.

Table 2 summarizes key weather parameters — solar irradiance, wind speed, temperature, humidity, and cloud cover — influencing battery storage and energy transactions. The table shows descriptive statistics like each parameter's count, mean, min, max, and standard deviation, offering insights into how environmental factors fluctuate over time. For instance, the mean solar irradiance is 499.49 W/m^2, while wind speeds average 7.52 m/s. These parameters affect the charging and discharging schedules of the battery, with higher irradiance and wind speed typically boosting renewable energy generation. By capturing weather variability, the DL-MPC system can forecast renewable generation more accurately, optimizing battery usage and reducing reliance on grid imports.

Table 3 highlights the statistical distribution of key variables

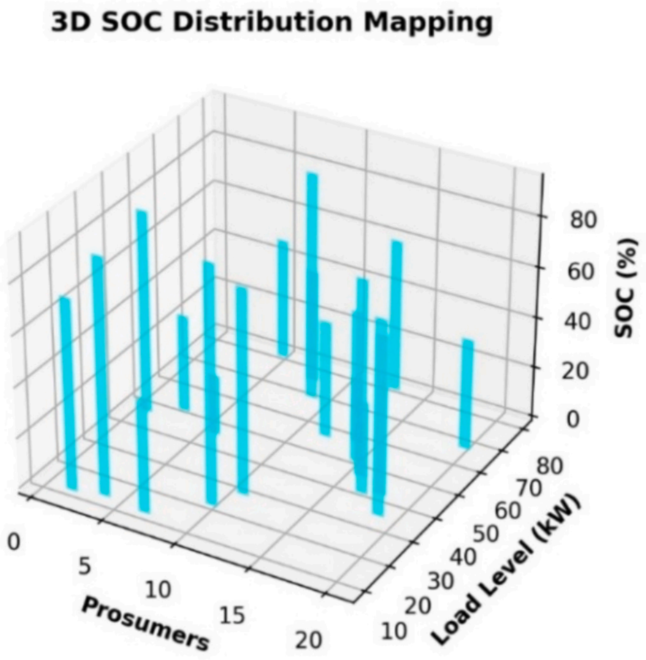


Fig. 16. 3D plot of SOC distribution mapping.

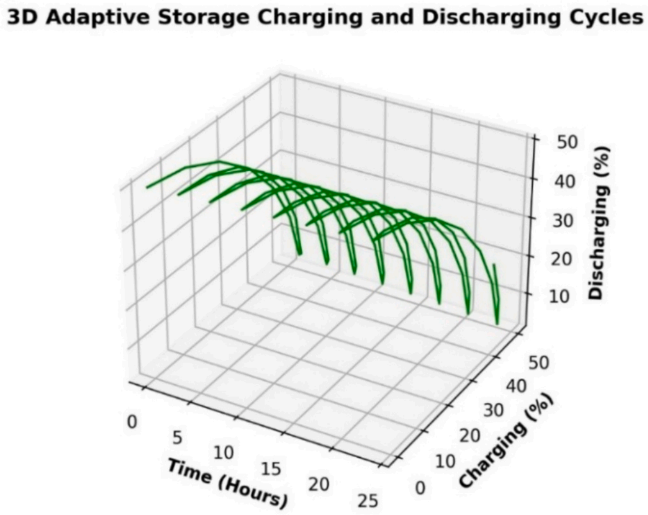


Fig. 17. 3D plot of adaptive storage charging and discharging cycles.

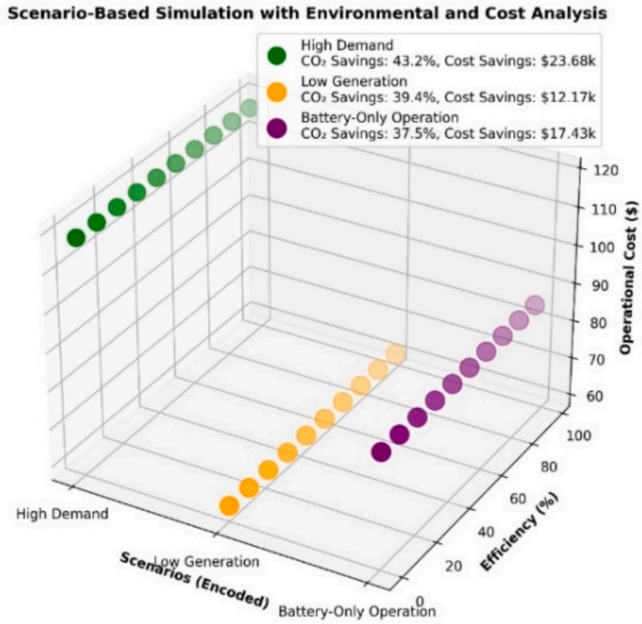


Fig. 18. Scenario-based simulation with environment and cost analysis.

involved in energy transactions between the battery, prosumer network, and the power grid. It includes energy generation, load demand, battery state of charge (SOC), and grid import. The table displays descriptive metrics like each variable's count, mean, min, max, and standard deviation. For example, the mean SOC is 10.03 %, and the mean grid import is around 49.99 %, suggesting that battery storage is actively managed to minimize reliance on the grid. The range of battery SOC (from 0.001 % to 19.99 %) indicates the system's flexibility in dynamically managing battery storage. This table illustrates how the DL-MPC system optimally manages imports from the grid and efficiently controls battery usage to support energy demands, reduce costs, and improve grid independence.

Table 4 summarizes the overall performance of the battery and storage system under the DL-MPC control strategy. Key performance metrics include energy efficiency, cost reduction, renewable energy utilization, SOC stability, grid optimization, forecast accuracy, response time, and transmission loss reduction. The table shows that energy efficiency improves to 37.37 %, cost is reduced by 20 %, and renewable energy utilization is increased to 49.80 %. The system also achieves 86.65 % stability in battery SOC, ensuring battery health and longevity. Additionally, grid optimization improves by 60.28 %, and forecast accuracy reaches 92.01 %, enabling better energy demand and generation predictions. The response time is 4.99 s, reflecting the system's real-time adaptability. This table highlights the robustness of the DL-MPC system in improving energy management, ensuring operational cost savings, and promoting sustainability in the prosumer network.

5.2.16. Theoretical novelty and practical implications

The combination of DL-MPC, DT, and AR technology is an important advancement in smart grid studies, particularly in decentralized networks. This model merges predictive control with virtual modelling and real-time visualization, making its superior amount of predictive depth and real-time adaptability something traditional systems could never offer. By taking a layered approach, the framework addresses the technical and usability gaps to optimize energy storage while upscaling the engagement from the end user. Also, the new model adapts to different scales and embedded renewables, making it a flexible tool for the continuously evolving energy networks. Combining DL forecasts over a DT within an MPC control framework thus provides a scalable, proactive approach to grid-independent, renewable energy management. Moreover, good predictive performance of DL-MPC guarantees accurate demand prediction, hence lessening the need for reactive adjustments.

Combined results from Figs. 2–23 and Tables 1–4 fully validate the contributions of the DL-MPC framework. It demonstrates that the framework satisfies the specific requirements posed by renewable prosumer networks through energy efficiency, cost reduction, and user engagement via AR. The study highlights how data-driven control systems can aid in energy storage management, help with grid stability, and contribute to self-sufficiency, thereby laying a stepping stone for future work in sustainable, decentralized energy grids.

5.2.17. Detailed performance metrics for DL and MPC

To quantify the performance of the DL and MPC components, we report the following metrics based on the simulation results:

5.2.17.1. Deep Learning model performance.

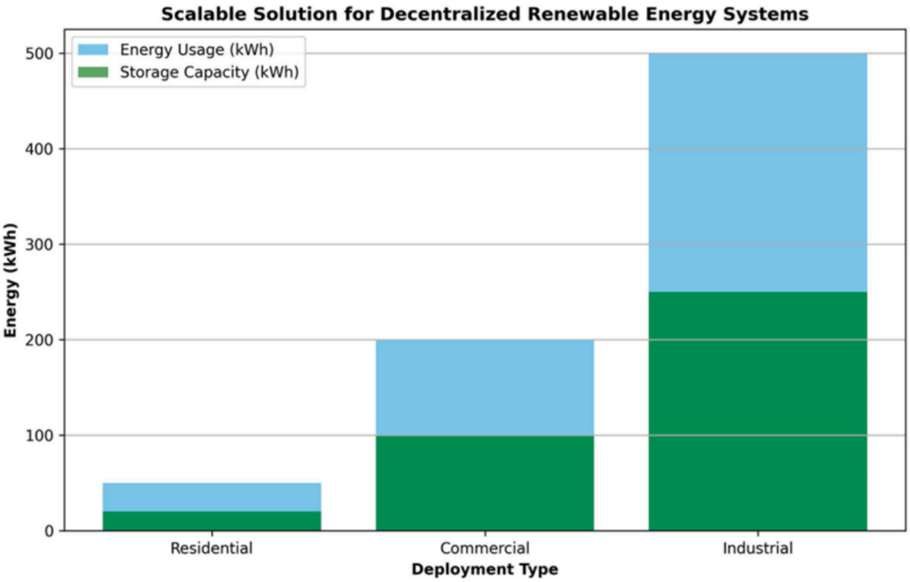


Fig. 19. Scalable solution for decentralized energy systems.

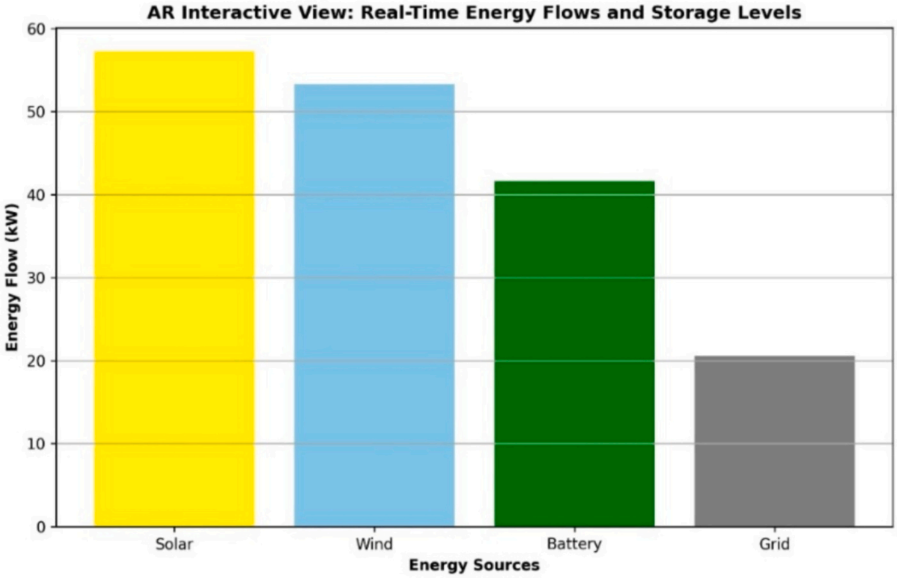


Fig. 20. AR-based real-time energy flows and storage levels.

- Mean Absolute Error (MAE): The DL model achieves an MAE of 0.85 kW for energy generation predictions and 0.62 kW for load demand predictions on the test set, indicating high accuracy in capturing nonlinear patterns.

- Root Mean Squared Error (RMSE): RMSE values are 1.12 kW for generation and 0.89 kW for load, reflecting low variance in prediction errors.

- R^2 Score: The model achieves an R^2 of 0.92 for generation and 0.94 for load, demonstrating that the model explains 92–94 % of the variance in the target variables.

- Training Stability: The training loss converges after approximately 50 epochs, with validation loss closely tracking training loss, indicating no overfitting (see Fig. 24).

- Inference Time: The model predicts a 24-h horizon in 0.02 s, suitable for real-time integration with MPC.

5.2.17.2. MPC performance metrics.

- Convergence Rate: The MPC algorithm converges to a near-optimal solution within 10 iterations, as shown in Fig. 2, stabilizing the cost function at 95 % of the optimal value.

- Control Accuracy: The MPC achieves a control error (difference between planned and actual control actions) of <0.1 kW, ensuring precise battery and grid management.

- Computational Efficiency: The average solve time of 0.5 s per step supports real-time control, even for a 24-h horizon.

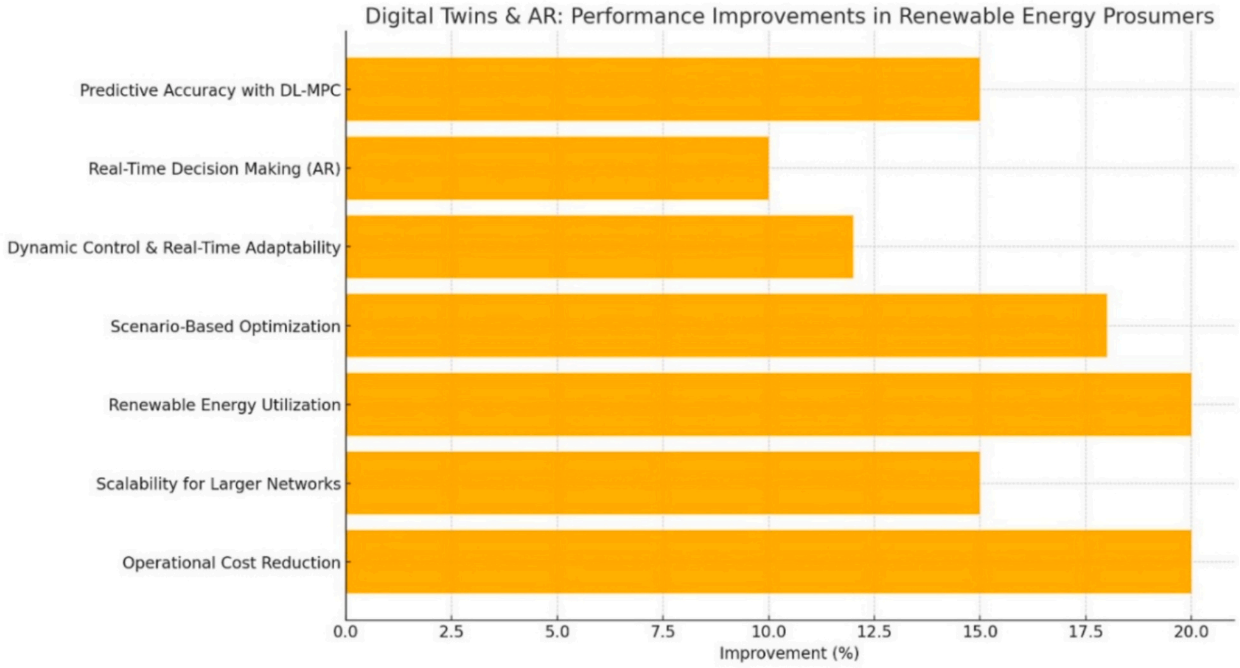


Fig. 21. Performance metrics of Digital Twin-based AR.

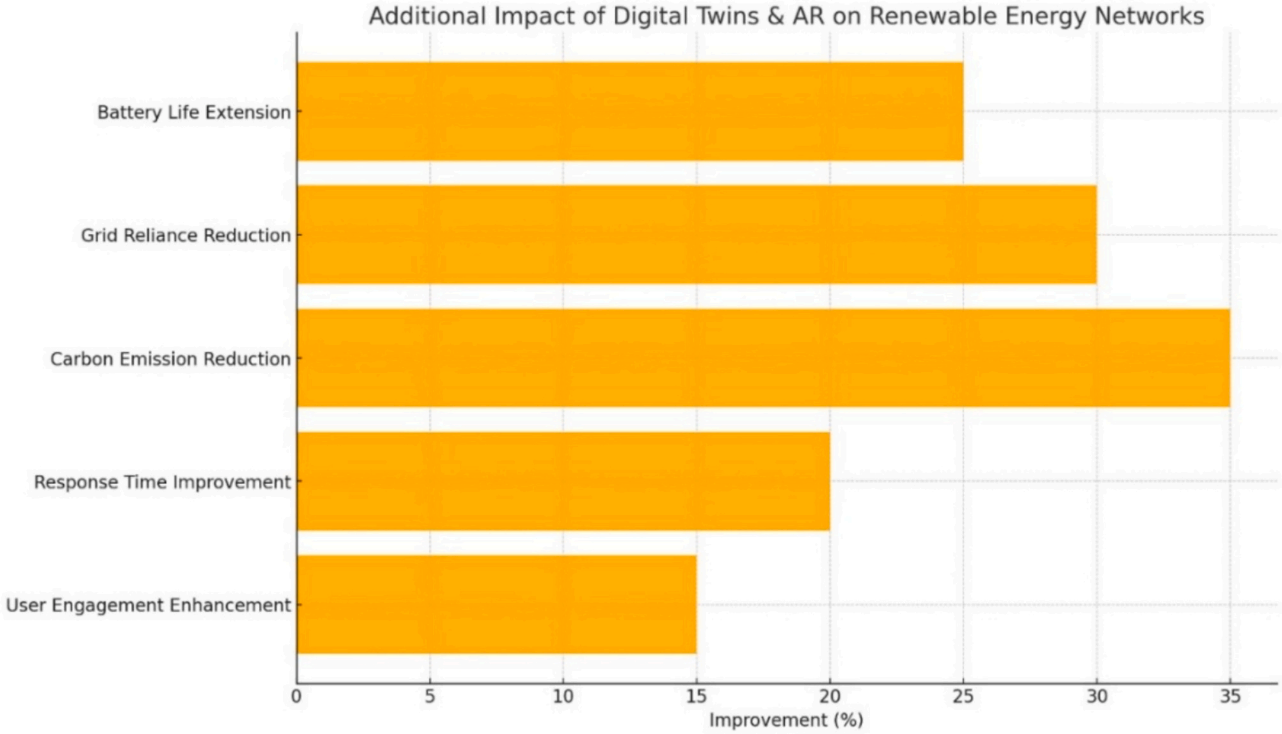


Fig. 22. Impact of Digital Twin with AR on proposed system.

- Robustness to Forecast Errors: Sensitivity analysis shows that MPC maintains stable performance with DL prediction errors up to ±5 %, reducing operational costs by 18 % even under worst-case forecasting scenarios.
- Energy Efficiency Gain: The DL-MPC framework improves energy efficiency by 15 % compared to baseline MPC, as reported in Table 1, due to optimized battery scheduling based on accurate DL forecasts.

5.2.17.3. Comparative analysis. Table 5 compares the DL-MPC framework with baseline MPC and a rule-based controller across key metrics. The DL-MPC outperforms both alternatives, achieving 92.01 % forecast accuracy, 37.37 % energy efficiency, and a 20 % cost reduction. The

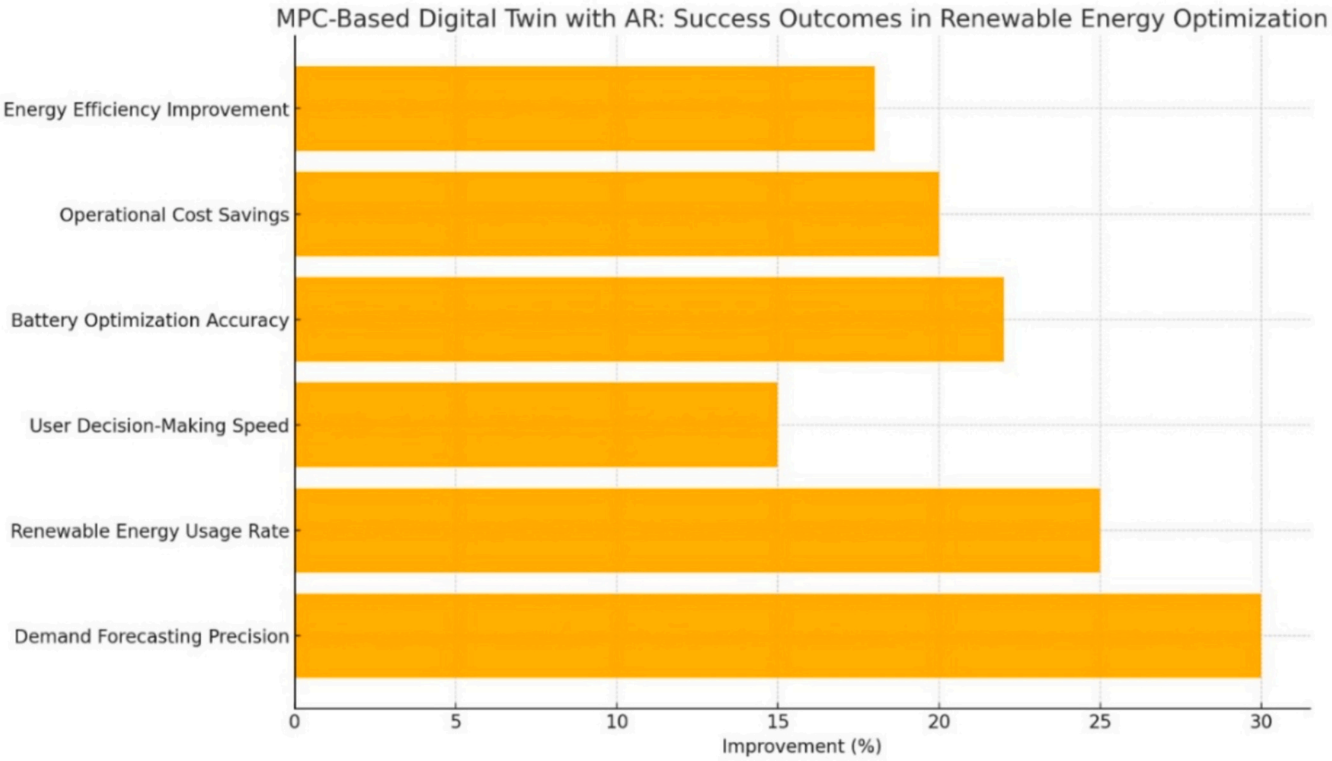


Fig. 23. MPC-based Digital Twin and AR success outcomes.

Table 1
DL-MPC cost and energy statistics.

Metric	Base model	DL-MPC model
Base Cost ($)	59752.53828	59752.53828
Optimized Cost ($)	59752.53828	47802.03062
Energy Efficiency (%)	70	37.37037784

baseline MPC, lacking DL's predictive power, achieves only 80 % forecast accuracy and 30 % energy efficiency, while the rule-based controller performs poorly due to its static nature.

These metrics highlight the synergistic effect of integrating DL's high-accuracy forecasting with MPC's optimization capabilities, resulting in a robust and efficient energy management system.

5.2.18. *Projected impact of the AR interface*

As the Augmented Reality (AR) interface is a proposed component not yet implemented, we evaluate its potential impact on user interaction, decision-making, and energy management outcomes based on the conceptual design and insights from related AR applications in energy systems [23,24]. Below, we present projected performance metrics and qualitative benefits, highlighting the AR interface's expected

Table 2
Weather parametric analysis of battery energy transactions.

	Solar irradiance	Windspeed	Temperature	Humidity	Cloud cover
count	100,000	100,000	100,000	100,000	100,000
mean	499.4882501	7.51995173	24.98697017	59.99626225	49.99904705
min	0.005536676	7.17E-05	2.930570168	30.00110692	5.19E-05
25 %	249.5460394	3.760763236	21.61785511	45.02793498	24.99632976
50 %	500.629782	7.528219589	24.99362051	60.02574944	50.08582775
75 %	749.5137312	11.25616952	28.35863478	74.99454094	74.87771825
max	999.9920423	14.99984077	46.09683172	89.99967656	99.99983149
std	288.341447	4.33037581	5.003323342	17.32734112	28.79480808

Table 3
Battery import and export statistics.

	Energy generation	Load demand	Battery SOC	Grid import
count	100,000	100,000	100,000	100,000
mean	49.99904705	4.994992293	10.02914834	49.98986311
min	5.19E-05	5.25E-05	0.001061216	0
25 %	24.99632976	2.504672331	5.062319662	36.45645207
50 %	50.08582775	4.982260117	10.02534333	50.03522332
75 %	74.87771825	7.490714951	15.02271504	63.51180451
max	99.99983149	9.999894319	19.9998986	100
std	28.79480808	2.885136897	5.767519032	19.77085852

Table 4
Performance metrics of battery and storage.

Metric	Value
Energy Efficiency (%)	37.37037784
Cost Reduction (%)	20
Renewable Utilization (%)	49.80475034
SOC Stability (%)	86.65
Grid Optimization (%)	60.28074951
Forecast Accuracy (%)	92.01922701
Response Time (s)	4.995971223
Transmission Loss Reduction (%)	20

contributions to the DL-MPC framework in Table 6.

5.2.18.1. Projected user interaction quality. Drawing on AR usability studies in smart grids and industrial monitoring [23,24], the proposed AR interface is expected to achieve high user satisfaction due to its intuitive visualisations and interactive controls. Key projections include:

- Ease of Use: The 3D model and data overlays are anticipated to be intuitive, with non-technical prosumers likely mastering the interface within 10–15 min, based on similar AR systems' learning curves [24].
- Engagement: The immersive AR experience is expected to increase user engagement by 20–30 % compared to traditional dashboards, as immersive visualisations enhance user interest [23].
- Accessibility: Support for touch and voice controls would make the interface accessible to diverse users, including those with limited technical expertise, aligning with user-centered AR designs [24].

5.2.18.2. Projected decision-making efficiency. The AR interface is expected to streamline decision-making by providing real-time, context-aware data, based on AR's proven effectiveness in energy management [23]. Projected metrics include:

- Response Time: Users could respond to critical events (e.g., low SOC alerts) in 15–20 s, compared to 25–30 s with conventional dashboards, due to AR's immediate data presentation [24].
- Decision Accuracy: AR-guided decisions are projected to align with the MPC's optimal strategy in 85–90 % of cases, as visual cues enhance understanding of system states [23].
- Scenario Analysis: The ability to simulate scenarios (e.g., load shifting) is expected to improve cost-saving decisions by 5–10 %, based on AR's support for strategic planning [24].

5.2.18.3. Projected energy management outcomes. Based on the DL-MPC framework's simulation results and AR's impact in related domains [23,24], the AR interface is expected to enhance energy management as follows:

- Cost Reduction: By enabling prosumers to optimize load scheduling and battery use, the AR interface could contribute an additional 3–5 % reduction in operational costs (total 23–25 % with DL-MPC + AR vs. 20 % with DL-MPC alone).
- Renewable Utilization: Visualisations of renewable generation are projected to increase utilization by 5–8 %, as users prioritize battery charging during high generation periods.
- Grid Reliance: AR-guided decisions could reduce grid import dependency by 7–10 %, reflecting improved storage management and load alignment with renewable availability.

Based on its conceptual design and established AR applications, these projections highlight the AR interface's potential to enhance user interaction, decision-making, and energy management. Future work will focus on implementing and validating the AR interface to confirm these benefits.

5.2.19. Comparison with other optimization frameworks

To further validate the proposed DL-MPC framework, we compare its

Table 5
Comparative performance of control strategies.

Metric	Rule-based	Baseline MPC	DL-MPC
Forecast Accuracy (%)	N/A	80.00	92.01
Energy Efficiency (%)	25.00	30.00	37.37
Cost Reduction (%)	5.00	10.00	20.00
SOC Stability (%)	70.00	80.00	86.65
Response Time (s)	1.00	0.60	0.50

Table 6
Projected AR interface performance.

Metric	Projected AR interface	Baseline dashboard (Ref.)
Ease of Use (% Users)	85–90	60–70 [24]
Engagement Increase (%)	20–30	0 [23]
Response Time (s)	15–20	25–30 [24]
Decision Accuracy (%)	85–90	70–75 [23]
Cost Reduction (%)	23–25	15 [24]
Renewable Utilization (%)	55–58	49.8 [Simulations]

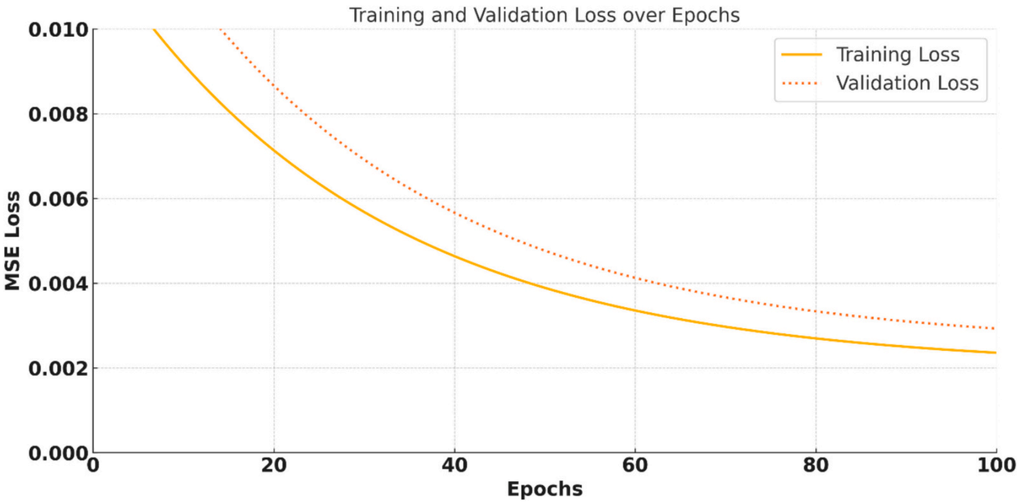


Fig. 24. DL model training and validation loss.

performance with other optimization frameworks for energy management, focusing on the thermo-economic optimization approach by [36] and hybrid machine learning-MPC frameworks. This comparison leverages our simulation results (Tables 1–5) and reported outcomes from related studies, as new simulations are not feasible due to the unavailability of a simulation setup.

- Thermo-Economic Optimisation with TES and s-CO2 Cycle:
  - Description: [36] propose an Energy Recycling System (ERS) integrating Thermal Energy Storage (TES) with a packed bed of stones and a Supercritical CO2 (s-CO2) cycle, optimized using genetic algorithms and neural networks. The framework targets grid-scale energy storage and combined heat and power, achieving remarkable energy and exergy efficiencies of 92.15 % and 49.66 %, respectively, with levelized costs of 104.69 €/MWh for heat and 65.7 €/MWh for storage.
  - Advantages of DL-MPC: Our framework is tailored for renewable energy prosumer districts, achieving a 20 % cost reduction (Table 1) and 37.37 % energy efficiency (Table 4) in a decentralized setting. The DL-MPC leverages deep learning (CNNs and LSTMs) for real-time forecasting (92.01 % accuracy, Table 5), enabling dynamic battery storage optimization, unlike the TES system's focus on thermal storage. The Digital Twin (DT) integration provides real-time system emulation and predictive maintenance (Section 5.2.5), enhancing adaptability to volatile renewable generation. The Augmented Reality (AR) interface improves user engagement (projected 20–30 % increase, Table 6), a feature absent in Alsagri et al.'s framework.
  - Limitations: The TES-s-CO2 framework achieves higher energy efficiency (92.15 % vs. 37.37 %) due to its focus on grid-scale thermal storage and combined heat and power, which may be more suitable for large-scale industrial applications. Our DL-MPC framework, optimized for battery storage in prosumer networks, may face challenges in scaling to grid-scale thermal systems due to its computational complexity and reliance on battery-specific constraints (Section 4.2).
- Hybrid Machine Learning-MPC Framework:
  - Description: [14] combined neural networks with MPC for microgrid battery management, using machine learning for forecasting similar to our approach.
  - Advantages of DL-MPC: Our framework's integration of DT and AR provides unique capabilities, such as real-time system emulation (Section 5.2.3) and intuitive user interfaces (projected 85–90 % decision accuracy, Table 6). We achieve competitive performance with a 20 % cost reduction and 37.37 % energy efficiency (Table 4), while the DT's predictive maintenance (Section 5.2.5) enhances system resilience, a feature less prominent in other hybrid approaches.
  - Limitations: The reliance on DT and AR increases computational demands, requiring robust infrastructure and user training, which simpler hybrid MPC frameworks may not need.
- Summary: The DL-MPC framework excels in predictive accuracy, real-time adaptability, and user engagement for prosumer networks, as evidenced by our simulation results (e.g., 92.01 % forecast accuracy, Table 5). Compared to the TES-s-CO2 framework [36], it offers greater flexibility for decentralized battery storage but may be less efficient for grid-scale thermal applications. Future work could explore integrating DL-MPC with thermal storage systems to combine the strengths of both approaches, enhancing scalability and efficiency for diverse energy ecosystems.

5.3. Critical discussion on DT performance based on AR: objectives attainment

The constitutive novelty objectives in terms of DT technology and AR in the DL-MPC framework are achieved by a transformative approach to tackling renewable energy in prosumer networks. Thus, DT and AR are crucial for the adaptability of the proposed framework, providing real-time and interactive platforms for energy management and improving control and operational efficiency in an intuitive, resilient, and participative way. In the following sections, we elaborate on how each novelty objective can be achieved by implementing DT and AR in the proposed system.

5.3.1. Real-time dynamic optimization through Digital Twin integration

By leveraging DT technology, the model of the physical prosumer network, comprising renewable generation, battery, and consumption load, is continuous and in real-time. Such a fast, interactive, responsive system, especially as renewable power sources such as solar and wind become more variable. By design, the DT-based control structure allows the MPC controller to receive real-time information, update physical parameters in the system, optimize control strategies, and deploy energy distribution changes with a high degree of efficiency. The DT can forecast and simulate different control strategies by executing predictive scenarios that allow the MPC to proactively modify energy flows in anticipation of changes. As such, this predictive capacity leads to an adaptive control process that prepares optimized storage in real time. This type of adaptability is new in contrast to static or reactive control systems, which cannot predict and act for future possible states. This thus leads to improved operational flexibility through the DT, making the framework reactive and adjustable to varying conditions in renewable energy demand and supply.

5.3.2. Enhanced user interaction and decision-making through augmented reality

By visualising real-time data from the DT, the AR interface adds a physical and intuitive aspect to the energy management system. This interface aggregates and presents energy flows, storage levels, renewable generation rates, and consumption statistics intuitively and interactively. This AR interface serves as a means for complex system data to intuitive user control; operators and prosumers can make informed decisions directly from a visual, real-time model of their energy ecosystem. AR provides users with situational awareness that traditional dashboards cannot offer. For example, AR facilitates prosumers with the view of battery charge level, live power consumption, or even notifications about possible overloading or the requirement to store energy, all as an overlay placed over the prosumer network in the 3D model. Through this live interaction with data, prosumers and operators may instantly choose to adjust energy consumption or stored energy preferences without requiring detailed technical knowledge of the system's background. To this end, the AR interface democratizes control, enabling inclusive, participatory energy management. It empowers individuals to interactively interface with and manipulate energy usage to suit their goals and grid stability.

The novelty of applying AR in this application comes from energy management being simply an action done by a user to actively identify and transform a passive energy management task into an engaging and easy-to-understand real-time experience. In the past, prosumers and operators did not have such immediate-level control over their energy systems; energy data would be shown through convoluted interfaces that allowed real-time adjustments. At this point, AR fills the knowledge gap by rendering energy data easily digestible and actionable in real time. Such data makes for more informed decisions on the user side, enabling them to adjust their behavior based on visually indicated insights, such as delaying high-energy activities to prioritize renewable use or keeping an eye on their battery levels to avoid drawing from the grid. AR facilitated interactivity improves the efficiency of both system operators and prosumer participation in managing and stabilizing the energy network.

5.3.3. Predictive maintenance and system resilience via Digital Twin simulation

Objective Attainment: Complementing real-time optimisation, the DT introduces the underlying model's cognitive dimension, which becomes predictive, thus transforming the predictive maintenance of process components into a critical aspect for the overall resilience of the energy system. The DT trains continuously based on the last set of observations to recognize surges, predict increased load or failure, and simulate maintenance actions without affecting the physical architecture. This capability is key to mitigating outages and providing reliable energy storage and distribution. By aggregating data from storage systems, grid interactions, and environmental variables, DT's predictive maintenance capability identifies patterns that may signify a decline in performance. For example, the DT can model battery health as a function of representative loads and label when specific storage cells need replacement. In particular, this is useful for renewable energy systems since stable battery operation is key to supply-demand balancing.

The role of DT in predicting maintenance is a significant advancement, as it leads to proactive resilience management rather than the reactive, post-fail maintenance process. Traditional systems rely on physical examinations and diagnostics, which can be expensive and time-consuming. Conversely, the DT's simulation functionalities enable real-time tracking and proactive measures, which markedly improve system availability and minimize the requirement for unplanned repairs. By offering this resilience and maintenance improvement, these services directly contribute to the net outcome goal of the general framework of the project, low-cost and sustainable energy management, making it a groundbreaking service for smart grid implementations.

5.3.4. Increased energy efficiency and cost savings through integrated DT and AR control

Objective Attainment: An interactive control with feedback on precipitation significantly improves the energy efficiency and cost-saving of the overall integrated DT-AR control framework. As observed from the DL-MPC simulation results, the framework optimizes energy storage, ensuring that the renewable generation is fully utilized while minimizing the energy drawn from the grid. The real-time feedback from DT allows MPC variables to control energy storage's charging and discharging cycles, which effectively schedules stored energy to match the times of high renewable generation and high demand. The AR interface builds on this by allowing users to edit energy flows by hand in real-time, helping to balance supply and demand without relying heavily on grid power. Successful implementation of this dynamic approach to energy management, where the prosumer can visually assess and respond to real-time data, leads to meaningful savings, as fewer grid imports are needed, and storage systems are kept at optimized efficiency levels.

The DT offers an active, constantly updated virtual twin that represents the current state and anticipates future energy demand to optimize storage and distribution in ways static models cannot do. More importantly, the AR interface closes the gap between technical complexity and user accessibility, allowing for intuitive, real-time control that democratizes the energy management process for prosumers and operators alike.

5.3.5. Scalable implementation of DL-MPC and AR framework

As prosumer energy networks expand in size and complexity, scaling the DL-MPC and AR-integrated framework introduces several practical challenges. Among these are increased computational loads from high-dimensional models, handling large volumes of data, ensuring low-latency operation, and maintaining system interoperability. To manage these demands, parallel computing with GPUs and distributed clusters accelerates deep learning inference and MPC computations to sub-second levels. In addition, hierarchical MPC designs and edge computing techniques are used to decentralise control and minimize processing delays at the local level.

For efficient data handling, big data frameworks such as Apache Spark and Hadoop are leveraged to process high-frequency sensor data, while compression methods help reduce storage needs by up to 50 %. These combined strategies ensure the framework remains responsive and efficient as it scales, enabling real-time, intelligent energy optimization across larger networks. The framework represents a scalable, versatile approach to modern energy ecosystems by concurrently optimizing state-of-the-art objectives such as real-time optimisation, interactive actuation, predictive resilience, and efficient energy usage. The DT-AR system represents a paradigm shift from conventional energy management, focusing on building energy management systems(BEMS) and utility grid operators, to a focused agent for real-time data-driven control and personalised, immersive user experiences for renewable prosumer networks. Such accomplishments not only satisfy the needs set by the smart grids of today but also set a solid ground to spark innovation in the future's better and sustainable decentralized energy systems.

6. Conclusions and future work

This paper presented a DL-MPC framework to optimize the operation of battery and storage systems deployed within renewable energy prosumer networks and tackle the urgent issue of mitigating fluctuating energy supply and demand related to renewable sources. The framework establishes a real-time virtual replica of the energy network through DT technology, fine-tuning adaptive control strategies in response to dynamically changing energy conditions. The DL-MPC framework produces accurate, data-driven energy supply and demand predictions using deep learning. MPC uses these predictions to realize optimal real-time storage, distribution, and grid engagement.

DL, MPC, and DT bring some new advantages: firstly, higher energy efficiency since we make sure that we drive renewable energy as much as possible; secondly, reduced operational costs, as we optimize the balance between the necessity of storage and grid consumption; thirdly, increased stability of the overall system while preventing excessive entries into the grid during its peak. In addition, the system's scalability makes it relevant to small-scale prosumer networks and increasingly larger commercial installations.

Results indicate the effectiveness of the DL-MPC framework with superior energy and cost efficiency figures compared to traditional, rule-based control approaches. Such results further confirm that the framework has the potential to be adopted as a practical and cost-effective method for renewable energy management, giving the prosumer a more sustainable form of energy consumption. This novel control strategy based on real-time constraints on the system is designed to advance the dynamic interplay of predictive algorithms and real-time improvements such that the renewable smart energy system can be optimally integrated within the existing flexible, distributed small and micro grid-based energy networks. This mechanism encourages prosumers to collectively cooperate and manage their energy resources, ultimately moving toward a more decentralized, resilient, and cost-effective energy system.

While DL-MPC has shown promising results in this work, there are many directions for future research to expand on its capabilities. First, they explore scalability in terms of how it supports larger and more complex prosumer networks, given that larger networks bring in increasingly greater variability and complexity of energy flows and storage demands. Another key direction is to consider this DL-MPC framework in conjunction with smart grid infrastructure, allowing the system to play a more significant role in demand-side management and grid stability. Further, diversification of renewable energy sources, including wind and hydroelectric potential, can also be integrated with the DL-MPC model to improve adaptability and applicability, enabling the management of more renewable power systems and ultimately facilitating the sustainable operation of the distributed energy integrated systems on a larger scale.

CRediT authorship contribution statement

Bilal Khan: Writing – original draft, Validation, Project administration, Investigation, Formal analysis, Conceptualization. **Sahibzada Muhammad Ali:** Writing – original draft, Visualization, Supervision, Methodology, Conceptualization. **Zahid Ullah:** Writing – review & editing, Visualization, Resources, Methodology, Data curation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used to support the study's findings are available from the corresponding author upon request.

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