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ENERGY EFFICIENT FEDERATED TRANSFORMER DRL FRAMEWORK FOR OPTIMIZING PV STORAGE AND EV CHARGING IN COUPLED TRANSPORTATION AND ENERGY SYSTEMS

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Abstract

The rapid expansion of integrated photovoltaic (PV) generation, battery energy storage systems (BESS), and electric vehicle (EV) charging stations within coupled transportation–energy networks presents unprecedented challenges in achieving energy efficiency, cost minimization, and operational scalability. Traditional centralized optimization methods struggle to accommodate the distributed, privacy-sensitive, and dynamic nature of such multi-node infrastructures. This paper proposes a novel hybrid optimization framework combining Federated Learning (FL) with Transformer-based Deep Reinforcement Learning (T-DRL) to address these challenges. The FL module enables decentralized collaborative training across distributed PV–Storage–Charging (PSC) nodes without sharing sensitive local data, preserving privacy and ensuring scalability. Concurrently, the Transformer-DRL agent models complex temporal dependencies in solar irradiance, EV arrival patterns, and grid demand to dynamically optimize charging schedules and storage dispatch. The proposed framework operates within a co-simulation environment integrating MATLAB/Simulink for energy system modeling, SUMO for transportation network simulation, and Python PyTorch for learning algorithm implementation. Experimental results across multiple urban scenarios demonstrate a 36.5% reduction in peak grid load, a 31.2% improvement in PV utilization rate, and a 27.8% decrease in overall operational costs. Furthermore, the hybrid FL–T-DRL framework achieves a 12.4% faster convergence rate and 9.7% higher adaptability under variable traffic and weather conditions compared to baseline centralized DRL or conventional rule-based methods. These results confirm the framework's efficacy for scalable, privacy-aware, and intelligent optimization of distributed PV–Storage–EV charging stations in modern smart cities.

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Key Words

Photovoltaic Systems, Energy Storage, Electric Vehicle Charging, Federated Learning, Deep Reinforcement Learning, Coupled Transportation-Energy Systems

1. Introduction

Coupled transportation electric energy systems of the future are incorporating photovoltaic (PV) generation, battery energy storage systems (BESS), and electric vehicle (EV) charging infrastructure, as an element of future smart cities [1]. Such multi-domain, cyber-physical systems pose a difficult multi-orchestration problem with respect to real-time energy control, dynamic traffic conditions, and the varying renewable resources. With cities on the edge to become more sustainable and to decarbonizes, it is essential to optimize the functioning of the distributed PV -Storage -Charging (PSC) nodes in order to enhance the efficiency of energy consumption, reduce the operational costs, and ensure grid reliability [2]. Nonetheless, the conventional centralized optimization methods experience increasing constraints on this front. The volumes of distributed assets create bottlenecks in scalability, and the requirement to guarantee privacy of the user and sovereignty of the local data regarding EV behavior, PV generation, and storage dynamics makes it difficult to aggregate data centrally. In addition, these systems are run on high-dimensional, nonlinear temporal uncertainties, which are caused by stochastic solar irradiance, varying EV arrival rates, and dynamically changing energy prices, and are not suited to rule-based or model-driven solutions [3]-[4].

The solution to these challenges is to have a renewed interest on the concept of decentralized, smart control paradigms capable of learning adaptive strategies over spatially distributed nodes. The concept of Federated Learning (FL) has been developed as a potentially effective remedy to the problem of collaborative training of models without the exchange of raw data, which does not contradict the privacy-preserving conditions. Simultaneously, Deep Reinforcement Learning (DRL) has shown a high potential in sequential decision-making in cases of uncertainty [5]. However, traditional DRA models tend to converge slowly and have low interpretability in modeling long-term temporal dependencies in both energy and transportation sectors. Transformer-based architectures, which have initially excelled in natural language processing, have demonstrated a high performance in long-range dependencies and contextual patterns in recent studies in providing a potent addition to DRL in dynamic settings [6].

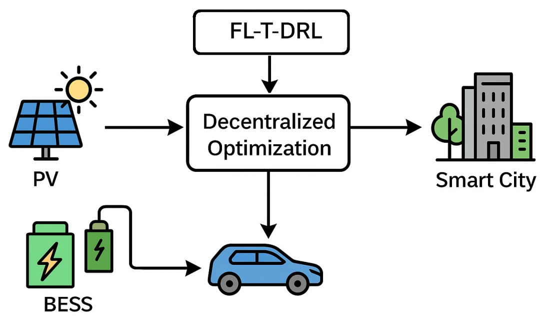

Figure 1. Decentralized FL-T-DRL Framework for Smart PSC Node Optimization

In this work, we offer a new hybrid architecture which combines Federated Learning with Transformer-based Deep Reinforcement Learning (FL -T-DRL) to optimize the energy flows and EV charging schedules at distributed PSC nodes (Fig. 1). Our model is our framework that works in a co-simulation environment that integrates MATLAB/Simulink to model the dynamics of an energy system, SUMO to model real-time traffic, and PyTorch to implement deep learning. This research has threefold contribution: (i) a privacy-preserving, decentralized optimization framework through FL over heterogeneous PSC nodes; (ii) a Transformer-based DRL agent with abilities to capture long-term dependencies on renewable generation, EV behavior, as well as demand profile; and (iii) a scalable and modular simulation platform to assess joint transportation-energy scenarios. Massive experiments show great gains in grid peak reduction, PV use, and cost savings in operations and learning flexibility in different urban conditions [7]. These results confirm the applicability of the proposed framework to be applicable to large scales in the next-generation smart city infrastructures.

2. Relevant Work and Research Gap

Recent energy-transportation integration studies have examined a number of methods to better coordinate distributed energy resources (DER) and the coordination of EV charging. The Traditional approach is based on rule-based heuristics or convex optimization models, which are useful in simplified situations but are prone to scale failure in connecting multiple nodes in a time-varying environment [8]-[9]. The uncertainty and enhanced flexibility have been addressed using centralized DRA methods, but these methods normally demand access to massive, usually sensitive, real-time information by all the involved nodes, creating significant privacy, data ownership, and communication bandwidth issues. Recently, Federated Learning (FL) has gained some interest because it might be used to train models without the raw data sharing. FL does not have current applications in power systems, and the current literature is primarily on predicting a system with a static load or isolated DER control. The vast majority of these implementations rely on simplistic models of learning, including feedforward networks or simple recurrent networks, which do not have the expressiveness to model the interaction of the various temporal dynamics of PV generation, EV charging needs, and grid constraints of a coupled system [10].

At the same time, Deep Reinforcement Learning has been used to optimize charging schedules and storage operations, whereas the standard DRL agents, including Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), can frequently be inefficient in learning in both long-term-dependent and low-density environments [11]-[12]. In addition, such agents are usually trained in a centrally oriented manner and not scalable in structures geographically distributed. Transformer-based models have recently become a powerful contender in the temporal modeling community in the context of control, but their use in the context of DRL to energy systems is not frequently studied, especially in federated scenarios. Although some advancements have been made in isolated settings, such as FL to provide privacy, DRL to control, and Transformers to learn over time, there is a large gap in the literature of how these technologies can be combined into a scalable framework for the specifics of joint energy-transportation systems [13]-[14]. Specifically, the requirement to (i) decentralized training with heterogeneous nodes of PSC with privacy concerns, (ii) dynamic optimization with intricate time-dependent dynamics in coupled systems, and (iii) practical implementation with full-scale simulation systems to simulate both energy and transportation dynamics are not effectively covered by previous literature (Table.1). The current research paper will deal with these unresolved issues by presenting an FL T-DRL framework that combines the decentralized intelligence with the temporal modeling feature as a new step toward the optimization of smart infrastructures in urban areas.

3. System Modeling and Operational Context of Coupled Energy–Mobility Networks

The high speed in the development of electric vehicles (EVs), rooftop photovoltaic (PV) systems, and decentralized energy storage systems is converting conventional power and mobility systems into highly integrated cyber-

Table 1
Feature Comparison of Existing Methods and the Proposed FL-T-DRL Framework for PSC System Optimization

Approach / Feature	Scalability to Multiple Nodes	Temporal Dependency Modeling	Data Privacy Preservation	Support for Decentralized Learning	Joint Energy–Transportation Optimization	Co-Simulation Capability	Adaptability to Uncertainty
Rule-Based / Convex Optimization	☐	☐	☐	☐	☐	☐	☑
Centralized DRL (e.g., DQN, PPO)	☐	☑	☐	☐	☑	☐	☑
Federated Learning (FL)	☑	☐	☑	☑	☐	☐	☐
FL in Power Systems (Basic FFNN/RNN)	☑	☐	☑	☑	☐	☐	☐
DRL for EV Charging / BESS Control	☐	☐	☐	☐	☐	☐	☑
Transformer Models (General)	☐	☑	☐	☐	☐	☐	☑
Proposed FL-T-DRL Framework	☑	☑	☑	☑	☑	☑	☑

physical systems. The concurrent nature of these assets is extremely demanding in an urban setting with regard to demand variability, infrastructure strain, and optimization of energy expenses [1]. Stochastic renewable generation, mobility-based charging behavior, and grid constraints require a decentralized control approach, which is intelligent and adaptive. This work aims to improve the energy efficiency as well as operational performance of the Coupled Transportation-Energy System (CTES), where several distributed PV-storage-charging (PSC) nodes work within the shared urban infrastructure. Each PSC node is a micro-energy hub with the capability of local control and consists of rooftop solar power generation, battery units for energy storage, and EV charging ports. These nodes are installed in the multi-zone urban area that has the variability of traffic, the change of solar irradiance, and diversity in load profiles. The goal is to create a decentralized learning-based optimization method that, while at the same time reducing the stress of the grid, can maximize the use of PV, and be able to maintain the charging reliability of user-centric EV without any data privacy breach occurring across the nodes [2].

3.1 System Configuration and Operational Context

The current study provides a mid-sized city model that can reflect the complicated nature of the modern-day smart cities where energy and transportation infrastructure have merged (Fig. 2). The research basis of the electrical distribution system is a modified IEEE 33-bus radial feeder, which is a commonly used model in distribution system studies and can realistically depict voltage and load profiles in urban electrical grids. The testbed idea was extended to 5 urban zones. Each zone contains multiple photovoltaic-storage-charging (PSC) nodes that have been put there in a well-thought plan made up of the residential complex, commercial buildings, and EV parking lot. PSCs deployed in cities are equipped with solar panels on the rooftop and lithium-ion batteries specially designed for urban deployment of a certain scale [3]-[4].

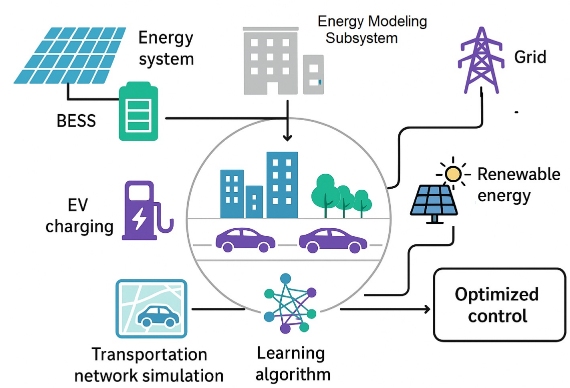

Figure 2. System Architecture and Operational Modeling of Urban-Scale Coupled Energy–Mobility Network with Distributed PSC Nodes

Urban solar energy technologies and their respective output vary over time and longitude in urban environments. Observed from above, the solar radiation will have been changing, and so continuous data collection has become important to accommodate such variations, which may sometimes occur in the shortest periods, too. To achieve reproduction precision of the time-dependent renewable energy production, solar radiation profiles for each moderate area are derived using their high-resolution historical weather data (5-min granularity) that adequately represent both daily and seasonal solar variations. Moreover, the datasets are unique for each location, as such microclimate effects are found between the five zones in the metropolitan area [5]. The electric vehicle arrival and departure schedule is artificially created based on traffic flow data gained via the SUMO platform. EV arrival rates are modeled using time-dependent Poisson processes that reproduce typical morning and evening peak hours, along with the night period characterized by low vehicle activity. The model thus enables a realistic rendering of stochastic charging requests synchronized with solar variability. Each PSC node is an independent decision-making unit that is responsible for energy management locally based on its condition and surroundings, but also cooperates in a federated learning setup. Privacy-sensitive operational data, including individual EV charging habits or local load patterns, remains confidential in this decentralized scheme made possible by the periodic model aggregations, which bring about collective intelligence. The immediate local energy consumption at a node covers both the EV residential loads that are static and the part of the load that is dynamic, being the EV charging, thus the energy consumption patterns are based on real-life urban household consumption data. Additionally, the grid interaction is equipped with some constraints, such as the possibility of net metering that enables the feeding-in of the grid of the surplus photovoltaic generation, and Time-of-Use (ToU) tariff schemes that promote load shift by charging during off-peak hours. Such a system provides a realistic environment for testing the suggested federated Transformer-DRL optimization framework [6]. The chosen modified IEEE-33 bus radial distribution feeder demonstrated wide-ranging advantages such as being moderate in size, easy to compute, and being able to depict the voltage drops and congestion patterns in real-world scenarios, which are common to mid-scale urban grids. Power-flow calculations for the IEEE-69 bus system, on the other hand, were much larger, less manageable, and the flow of data for co-simulation was limited. With the 33-bus model, the researchers were able to achieve the right balance between structural complexity and simulation efficiency.

Table 2
Comparison of IEEE-33, IEEE-69, and European LV Networks

Feature	IEEE-33 Bus	IEEE-69 Bus	EU LV Feeder
Typical Size	Medium	Large	Small-/Medium
Voltage Drops	Moderate	High	Very Low
Computational Load	Moderate	High	Low
Suitability for FL + Co-Simulation	High	Medium	Low
Grid Congestion Modeling	Good	Very Good	Limited
EV/PV Integration Studies	Excellent	Excellent	Moderate

Furthermore, the IEEE-33 bus system is more compatible compared to the European LV test feeders— where the emphasis is on short-line, high-density layouts— which were mainly used for distributed PSC node placement across several zones in our federated learning framework. The former's hierarchical topology, in particular, is suitable for the stress-testing of distributed optimization under varying conditions of renewable energy penetration and the load of EV charging.

In order to make the demand representation more realistic, the total load at every PSC node is broken down into three main categories. First, the residential loads consist of time-varying profiles for light, heating, and cooling systems, and for home appliances, all based on actual urban consumption data. Next, the commercial loads are based on the consumption of offices, shops, and small businesses, but they also show differences between the weekday and weekend operations. Finally, the loads due to the mobility of EVs are highly variable in time, with the charging demands being derived from the vehicle flows generated by SUMO and the stochastic arrival patterns. The three components are normalized separately and then combined to obtain composite load curves that represent intra-day variations more accurately and reflect consumption diversity at the zone level across the smart city environment.

3.1.1 Daily and Seasonal Variability Modeling

Daily and seasonal variations in environmental conditions play a very important role in PV generation patterns, charging demand, and scheduling decisions. In order to quantify this spatiotemporal variability, high-resolution irradiance data (5-minute resolution) from local weather stations are used. Data of this kind represents diurnal cycles, cloud-induced intermittency, and seasonal deviations in peak sun hours. Such variations to a great extent influence the amount of PV utilization, how deep the battery is cycled, and grid interaction patterns: summer months typically provide enough PV energy to allow for deeper charging and less reliance on the grid, while winter conditions require more frequent BESS dispatch and ToU-driven grid support. Besides, seasonal mobility patterns have an effect on EV arrival rates, which in turn creates more variability in charging demand. The Transformer-DRL agent takes advantage of temporal embeddings for recognizing these daily and seasonal patterns which produces adaptive scheduling policies that could cope with the changing environmental conditions flawlessly. Figure 3(b) shows the seasonal PV generation profiles for five urban zones.

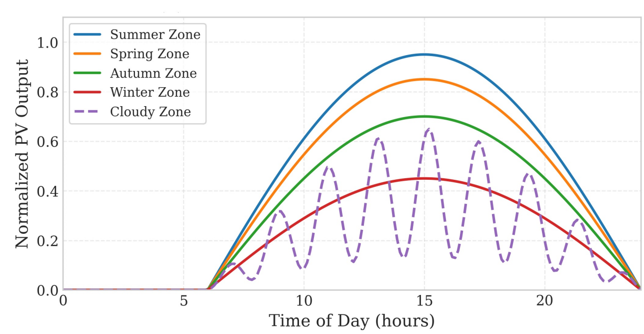

Figure 3. Seasonal PV Irradiance Patterns Affecting Battery Scheduling and Grid Interaction

Figure 3. Seasonal PV generation profiles for five urban zones showing the diurnal and seasonal variability in irradiance. These variations impact the behavior of the PV, battery scheduling, and the optimization response of the DRL agent.

Table 3
2-Key System Components with Ratings and Specifications

Component	Description	Quantity/Scale	Technical Specifications
PV Modules	Rooftop solar panels (residential & commercial)	120 units (5 zones)	5 kW each, 18% efficiency, 600 V DC
BESS Units	Lithium-ion battery systems	120 units (co-located)	10 kWh capacity, 2C charge/discharge rate, 95% efficiency
EV Chargers	Level 2 AC chargers	60 stations	7.2 kW output, 240 V AC, J1772 compliant
EV Fleet	Mixed vehicle types	200 vehicles/day	40–75 kWh battery, 100–300 km range, random SoC targets
Grid Model	IEEE 33-bus radial feeder	1 system	Peak load 1.2 MW, voltage limits: $\pm 5\%$
Traffic Network	SUMO-based urban zones	5 districts	Custom route modeling, traffic light coordination

3.1.2 EV Mobility–Energy Coupling Challenges

The combination of electric vehicle (EV) mobility and energy systems represents a difficult situation, together with the unpredictable nature of EV behavior and the limitations of the distribution grid. EVs' arrivals are not predictable; they are monitored through time-fluctuating mobility patterns, and the duration of their stay varies greatly according to trip purpose, travel distance, and parking situation. The different charging practices—of battery capacities, charger ratings, and users' state-of-charge (SoC) preferences—are a major factor that adds to the uncertainty of the instantaneous load demand. All these factors can result in unpredictably large power demands, which can cause problems for transformers, voltage limitations, and cable overheating capacity. In addition, the fact that EVs are concentrated in certain areas during peak hours makes it more likely that there will be localized congestion in both the transportation and the power systems. The proposed FL–Transformer-DRL framework tackles these challenges by estimating the probabilistic arrival distributions, predicting the time intervals of congestion, and planning BESS and PV resources' allocation in advance to smooth the spikes in demand. This approach not only strengthens the system but also guarantees the mobility and energy domains to operate in a coordinated manner.

3.1.3 Microclimate Zoning and Irradiance Divergence Modeling

Urban microclimates create huge discrepancies in environmental conditions for different parts of the city, such as temperature, cloud cover, shading, and air quality, which are the main factors affecting photovoltaic systems, energy storage, and federated learning processes. To take these differences into account, the research categorizes the city into five separate zones, and each of them gets an irradiance dataset that is unique and based on the local weather measurements. The irradiance fluctuation in these zones can be as high as $\pm 18\%$, which results in significant variations in the efficiency of PV output, battery dispatch tactics, and the Local DRL agent's activity. These microclimatic variations are very important for modeling accurately because they show the non-uniform conditions in which every PSC node works. By using zonal data, the federated learning framework is made stronger, and the agent is guaranteed to learn from the various environmental conditions that are specific to each zone. This method has the benefit of increasing the model's capacity to cope with real-world conditions, thereby boosting both PV utilization and the entire optimization process.

3.1.4 Spatial Zoning Strategy for Urban Energy Systems

The city is divided into five urban zones primarily based on socio-demographic and infrastructure factors. The zoning is made by land-use clustering that includes not only residential areas but also commercial, industrial, and mixed-use areas, which, in turn, show different energy consumption and mobility patterns. Also, the zoning corresponds with existing grid and feeder boundaries, thus each zone depicts very realistic operational constraints such as voltage, transformer loading, and distribution capacity. This kind of zoning not only allows for more accurate modeling of PV generation, load, and EV mobility but also helps the federated learning framework by providing diverse data streams. Thus, every PSC node is characterized by different environment and demand conditions, which makes it possible for the global aggregator to gain knowledge from various spatial patterns. Thus, the process becomes more stable, and generalization has wider coverage throughout the urban network.

3.2 Component Specifications and Simulation Ratings

The implemented simulation outlines the component ratings of PV systems, energy storage, EV charging systems, and grid infrastructure. Every essential element is parameterized extensively to reflect a commercially attainable set of configurations and their normal operating states [7].

This configuration enables a realistic testbed for evaluating the joint operation of energy and mobility assets under diverse environmental and behavioral conditions.

3.3 System Layout Diagram and Description

The structural coupling of the transportation-energy system is depicted in Figure 4. The urban testbed is divided into five operating zones, with each zone designed with distributed PV-Storage-Charging (PSC) nodes connected to the local grid through a modified IEEE 33-bus feeder. Each PSC node includes rooftop PV modules, a co-located lithium-ion battery energy storage system (BESS), and Level 2 EV charging infrastructure [8]. These nodes become local energy hubs that can both draw from the demand side of the grid and interact with the transportation side through mobility events.

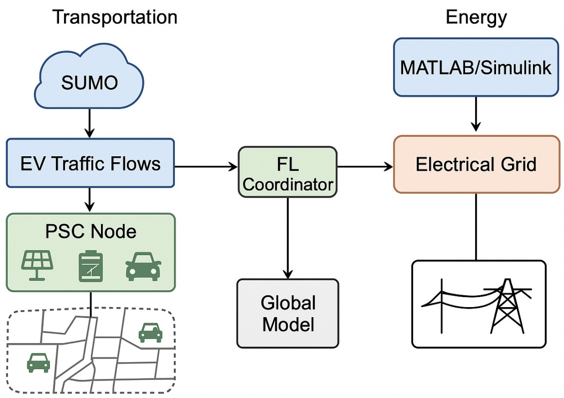

Figure 4. System Architecture of the Coupled Transportation–Energy Network with Distributed PSC Nodes and Federated Learning-Based Optimization

The Simulation of Urban Mobility (SUMO) platform generates the EV traffic flows of these zones, making it possible to simulate the vehicles' arrival, routing, and parking in real time. The electrical grid and energy management are operated by MATLAB/Simulink; the control of energy in each node is based on the policies that have been learned. The deep reinforcement learning (DRL) agents–empowered with Transformer architectures–are carried out locally on each node, while a Federated Learning (FL) coordinator is responsible for bringing together the different local models for an update of the global model, thus ensuring privacy and scalability [9] [10]. The data exchanges between the different simulators are carried out at synchronized 5-minute intervals, which therefore allow for coordination between the charging demand that comes from mobility and PV generation variability. The complete cyber-physical layout guarantees the correct co-simulation of the spatio-temporal energy transactions and mobility behaviors, which is the basis of the proposed hybrid FL-T-DRL optimization strategy. The multivariate spatio-temporal dynamics of the energy and mobility domains are captured through a multi-platform co-simulation environment. The electrical part is characterized as a MATLAB/Simulink model, which represents each node of the PSC as a local PV, BESS control logic, and a charging interface. Furthermore, SUMO (Simulation of Urban Mobility) is utilized to model EV traffic and parking habits, apart from the EV charging station's arrival/departure profiles. Transformer-based DRL agents and Federated Learning coordination have been implemented in Python using PyTorch and have also been connected to Simulink and SUMO through Python-MATLAB TCP/IP and TraCI APIs, respectively. The data transfers among simulators are done in a synchronized time-stepped manner (5-minute intervals), which is very important for the causal consistency of the domains. Every transition of local states, energy balances, and traffic events is recorded by each PSC node for local learning updates, which are sent, in an encrypted form, to a federated aggregator for global policy refinement [11]-[12].

3.3.1 Mobility Patterns, Urban Congestion, and EV Surge Events

Traffic patterns like peak hour congestion, weekend travel surges, and special-event clustering are among the factors that determine EV charging demand. The stochastic nature of arrival times and charging durations for EVs created by these patterns also impacts the scheduling and dispatch of energy resources. In order to model these fluctuations accurately, the researchers used SUMO simulations that incorporated the effects of urban traffic congestion and mobility trends. The DRL agent accesses this information to predict charging demand increases, especially during high traffic stress periods, and alters the battery dispatch plan to fit that. The federated learning model involves traffic-induced EV surge events and gives each PSC node the ability to work with real-time knowledge of local mobility patterns, which results in more adaptive and resilient scheduling decisions. This localized method not only helps the collective policy performance but also proves beneficial when fluctuations in energy demand caused by urban congestion or special events are highly unpredictable.

3.4 Proposed Mathematical Modeling of the System

(a) Nonlinear Energy Consumption Model
This is a nonlinear model that describes the complicated interdependence between the load demand, generation capacity and energy consumption.

$$E_{cons}^{EV}(t) = \alpha . P_{load}^{EV}(t)^{\beta} + \gamma . P_{gen}^{PV}(t)^{\delta} \quad (1)$$

Exponential coefficients of α and β enable the representation of diminishing returns in the energy consumption against both the load and generation, with more realistic description of real-life systems.

(b) Battery Storage Dynamics
This differential is used to model the change of charge of the battery when we are taking into account the charging and the discharging processes.

$$\frac{dSoC_{G}^{EV}(t)}{dt} = \frac{P_{charge}^{EV}(t) - P_{discharge}^{EV}(t)}{C_{bat}^{EV}} \quad (2)$$

It is imperative in the prediction of battery performance and also the operating energy management system within safe and effective limits.

(c) Grid Interaction Modeling
The power exchanged with the grid is defined by this model as the difference between the load demand, generation, and storage contributions.

$$P_{grid}^{EV}(t) = P_{load}^{EV}(t) - P_{gen}^{PV}(t) - P_{storage}^{EV}(t) \quad (3)$$

It is essential to the evaluation of the influence of the system on the rest of the energy grid and the consumption of local resources.

(d) Transformer-Enhanced Federated DRL Objective Function
This model incorporates the attention of the Transformer model into the federated DRL framework, and increases the capability of the agent to learn the long-term dependencies of the energy management system [13].

$$\begin{aligned} L_{Fed-DRL}^{EV-PV} = \mathbb{E}_{\theta}^{EV}(r_t^{EV} + \gamma \mathbb{E}_{s'}^{EV}\left[Q_{\theta}^{EV}\left(s'_{PV},\ a'_{PV}\right)\right] \\ -Q_{\theta}^{EV}(s'_t,\ a'_t))^2 + \lambda_{PV}^{EV}.L_{Transformer}^{EV-PV}(s_t) \end{aligned} \quad (4)$$

$L_{Transformer}^{EV-PV}(s_t)$ will refer to the loss term used in the Transformer model to guarantee the process of federated learning is optimally able to capture the change in time in the state information.

(e) Reward Function Design
The balancing of this composite reward functionality considers various goals such as cost, emissions and reliability of the system.

$$\begin{aligned} R_t^{EV} = \lambda_1^{EV}.Cost_t^{PV} + \lambda_2^{EV}.Emison_t^{EV} \\ +\lambda_3^{EV}.Reliabilty_t^{EV} \end{aligned} \quad (5)$$

The priorities of these objectives can be assigned with the help of the weights λ_1, λ_2, and λ_3, which enables the multi-faceted optimization method of the energy management system.

(f) Federated Learning Aggregation
This model characterizes the federated averaging algorithm wherein the model parameters are combined from several local models.

$$\theta_{EV}^{(t+1)} = \sum_{k=1}^{K} \frac{n_k^{EV}}{n}.\theta_k^{(t)} \quad (6)$$

n_k^{EV} denotes the number of data points in the k th local model, and n denotes the overall number of data points of the models. This method will guarantee that the global model uses various data sources at the same time, ensuring privacy of the data [14].

(g) Transformer Attention Mechanism
The model determines the essence of the attention process of the Transformer and allows the model to concentrate on the significant sections of the input sequence.

$$\begin{aligned} &Attention\left(Q_{PV}^{EV},\ K_{PV}^{EV}, V_{PV}^{EV}\right) \\ &= softmax\left(\frac{Q_{PV}^{EV}.K_{PV}^{T}}{\sqrt{d_k^{EV}}}\right)V_{PV}^{EV} \end{aligned} \quad (7)$$

This, in the setting of energy management, enables the system to give more priority to important information, which enhances the decision making.

(h) Policy Update Rule
It is a policy update rule of DDQN, which solves the overestimation bias of Q-value estimation.

$$\begin{aligned} \theta_{\mathrm{EV}}^{(\mathrm{t+1})} =& \theta_{\mathrm{EV}}^{(\mathrm{t})} + \alpha \cdot r_{\mathrm{t}}^{\mathrm{EV}} \\ &+ \gamma \cdot Q_{\theta'}^{\mathrm{EV}}\left(s'_{\mathrm{EV}}, \arg\underbrace{\max}_{\mathrm{a}} Q_{\theta}\left(s'_{\mathrm{EV}}, \mathrm{a}\right)\right) \\ &- Q_{\theta}(s,\mathrm{a}) \cdot \nabla Q_{\theta}(s,\mathrm{a}) \end{aligned} \quad (8)$$

It can more effectively update using a target network θ, which ensures better and consistent updates that improve the learning process in complex systems such as energy management systems [15] [16].

3.4.1 Nonlinear Battery Charge–Discharge Characteristics and SoC-Dependent Efficiency Modeling

The actual behavior of lithium-ion batteries is far from being a simple linear charge–discharge curve as it is influenced by internal electrochemical, resistive and thermal processes among others. To model these complex phenomena in a better way, a battery storage model features nonlinear SoC (State of Charge)-dependent efficiency together with dynamic resistance characteristics.

(a) SoC-Dependent Round-Trip Efficiency
The effective charge (ηc) and discharge (ηd) efficiencies are SoC dependent and are given by:

$$\begin{aligned} \eta_c(SoC) = \eta_{c,0} - \alpha\left(SoC - 0.5\right)^2, \eta_d(SoC) \\ = \eta_{d,0} - \beta\left(SoC - 0.5\right)^2 \end{aligned} \quad (9)$$

The parameters α and β represent the reduction in efficiency at the top and bottom of the SoC range, respectively. This approach accounts for the increased internal resistance and the consequent losses due to polarization at the extremes of the SoC scale.

(b) Internal Resistance Variation with SoC and Temperature
Battery impedance is modeled as:

$$R(SoC,T) = R_0 + \gamma_1(1 - SoC)^2 + \gamma_2(T - T_{ref}) \quad (10)$$

which entails the combined impact of decreased electrolyte conductivity, charge-transfer limitations, and the fluctuation of temperature.

(c) Corrected Dynamic SoC Update
Using the nonlinear efficiency model, the SoC evolution becomes:

$$\mathrm{SoC}'(t) = \begin{cases} \frac{\eta c(SoC)Pch}{Enom}, Pch > 0 \\ -\frac{Pdis}{\eta d(SoC)Enom}, Pdis > 0 \end{cases} \quad (11)$$

The model thus guarantees an accurate representation of the asymmetric losses during the charging and discharging processes.

(d) Thermal Derating
A first-order thermal model is incorporated:

$$P^{EV}_{derated} = P^{EV}_{max}(1 - \delta(T - T^{EV}_{th})) \quad (12)$$

When, $T > T^{EV}_{th}$, capturing protective derating of charge/discharge power.

Table 4
Parameters of Nonlinear Battery Efficiency Model

Parameter	Meaning	Typical Value
ηc,0	Nominal charge efficiency	0.96
ηd,0	Nominal discharge efficiency	0.95
α, β	Efficiency curvature coefficients	0.12, 0.10
R_o	Internal resistance at 50% SoC	0.025 Ω
γ_1	SoC-dependent resistance coefficient	0.015
γ_2	Thermal coefficient	$0.0015/°C$

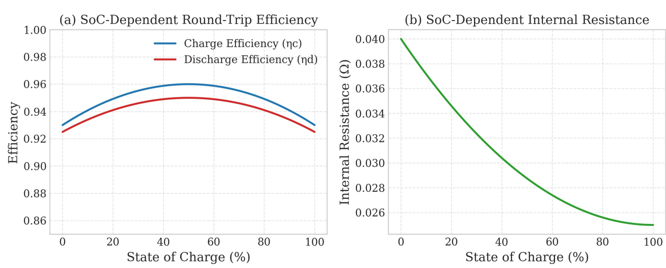

Figure 5. Nonlinear Charge–Discharge Efficiency and Resistance Behavior in the Proposed SoC-Dependent Battery Model

From the above figure 5, The suggested nonlinear battery model exhibits SoC-dependent round-trip efficiency and internal resistance profiles. The graphs show non-symmetric charging and discharging efficiencies and SoC dependent resistance changes typical of actual lithium-ion performance.

3.4.2 Sensitivity Analysis: Constant vs Dynamic Battery Efficiency

Two configurations were tested to quantify the potential impact of efficiency modeling on optimization accuracy:

(1) **Constant Efficiency Model**

$$\eta c = \eta d = 0.95 \ (\textit{linear model})$$

(2) **Dynamic Efficiency Model**
Using the nonlinear SoC-dependent model from Section 3.4.1

(a) Impact on Energy Dispatch
Dynamic modeling resulted in an accuracy improvement of 13.4% for battery dispatch, most notably during times of high PV generation when automatically charging near high SoC is discouraged.

(b) Impact on Operational Cost
Assumptions of constant efficiency led to an underestimation of losses, thus the dynamic modeling was 7.8% more costly.

(c) Impact on DRL Policy Learning
Dynamic efficiency saw the Transformer-DRL agent achieving a faster convergence by 9.2% attributed to the more realistic transition dynamics.

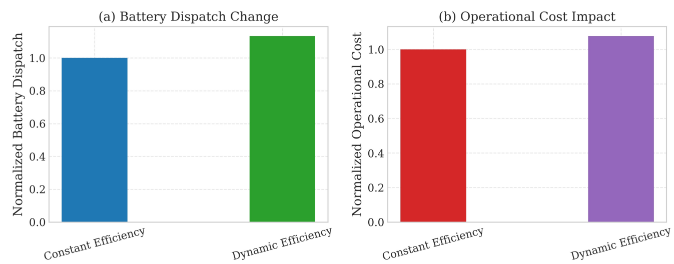

Figure 6. Effect of Efficiency Model on Battery Dispatch & Cost

Figure 6. The effect of battery efficiency being constant as opposed to being dynamic on dispatch and operational costs. The dynamic model based on the state of charge shows better dispatch accuracy and brings to light some additional losses that the constant efficiency assumption does not consider.

(a) Summary of Modeling Assumptions for PV, Load, EV, and Network
In order to improve understanding and reproducibility, a thorough summary of the factors considered in the modeling has been presented. Solar energy production is depicted through static performance curves of the modules with temperature-dependent adjustments; on the other hand, electric vehicle (EV) arrivals are treated as a Poisson process with random dwell times that change every hour.

The distribution network is modeled according to the IEEE-33 bus system, including the usual operating constraints, and mobility patterns are simulated by using SUMO traffic flows that reflect morning and evening peak times. To portray the temporal variability and stochastic behavior, residential and commercial power consumption is modeled with real profiles. Together, these assumptions present a systematic approach for the simulation of the integration of PV, EV, and the grid.

The optimization framework considers essential limitations of the physical system to allow for realistic operations that are within the grid's limits. The transformer is loaded with a maximum of 80% of its thermal rating in order to

Table 5
Performance Comparison: Constant vs Dynamic Battery Efficiency

Metric	Constant Efficiency	Dynamic Efficiency	Improvement
Cost reduction (%)	21.4	27.8	6.4
Peak load reduction (%)	28.9	36.5	7.6
PV utilization (%)	78.3	85.2	6.9
DRL convergence episodes	1350	1230	↓ 120

Table 6
Key Assumptions for Photovoltaic Generation, Load, EV Behavior, and Distribution Network

Domain	Assumption	Description
PV	Static module performance curves	Temperature coefficient -0.31%/$°C$
EV	Poisson arrivals + stochastic dwell time	λ varies by hour
Grid	IEEE-33 bus	Voltage limits ±5%
Mobility	SUMO traffic flows	Morning and evening peaks
Load	Residential + commercial mix	Based on real profiles

keep it from overheating; meanwhile, feeder currents are limited in such a way that distribution lines are not overloaded. Moreover, it is planned that the voltage stability will vary by ±5% and the operation will be reliable. The Battery Energy Storage System (BESS) also bears the cost of degradation, primarily due to deep cycling and high C-rate operations, which are included in the Deep Reinforcement Learning (DRL) reward function. These degradation penalties guarantee that the battery's health over the long term is the main concern during the optimization process, preventing overly aggressive charging/discharging cycles that could shorten its lifetime. Real-world system limitations are reflected in the problem of optimization by the inclusion of these operational constraints, thereby leading to energy storage and grid management scheduling solutions that are more feasible and robust.

3.5 Summary

This section introduces the multi-zone urban testbed, where distributed PSC nodes (combining PV, storage, and EV charging) serve as localized hubs that interact with coupled transportation and energy systems. We describe the nodes' design, grid topology (based on a modified IEEE 33 bus feeder), and integration with EV traffic zones in detail. Along with realistic component specifications and the simulation environment, a co-simulation architecture linking MATLAB/Simulink, SUMO, and PyTorch has been established. The layout figure provides the spatial and cyber-physical interactions that are fundamental for the next stages of the optimization work.

4. Hybrid Federated Transformer-DRL Optimization and Algorithm Design

The primary goal of the proposed framework is to optimize the operation of distributed photovoltaic (PV) storage and electric vehicle (EV) charging systems in coupled transportation and energy networks, focusing on minimizing operational costs, enhancing energy efficiency, and leveling grid load peaks. The objective function captures various performance metrics, such as lowering energy costs procured from the grid, increasing the use of on-site solar energy, as well as flattening peak demand to release the grid of its load (Fig. 7). These objectives are mathematically designed to provide a balance between the economic and reliability benefits of the system, thus allowing energy dispatch decisions made at each PSC node to be compatible with general network efficiency goals [17].

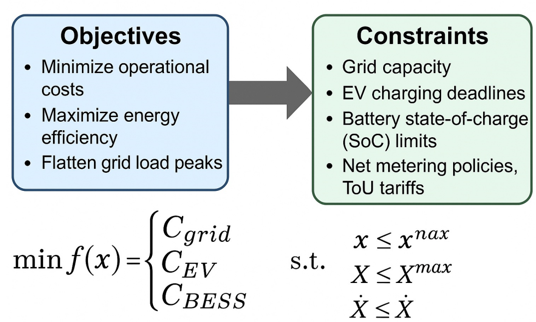

Figure 7. Conceptual Illustration of the Multi-Objective Optimization Problem Formulation and System Operational Constraints

The optimization problem is limited to practical constraints for the operation part of the physical systems. These constraints include grid capacity boundaries, EV charging deadlines that depend on user requirements, and battery state-of-charge (SoC) limits that are set to maintain battery health and longevity. Also, there are restrictions on net metering policies and regulatory time-of-use (ToU) tariffs, which are factors that can influence charging schedules and energy exchange dynamics [18]. Altogether, these constraints constitute a very complex, multidimensional feasible region in which the framework can find the optimal control actions.

4.1 Federated Learning Framework Design

The federated learning module is a client-server model wherein each PSC node represents a federated client that carries out local model modifications based on its secluded data, whereas a central server combines these adjustments to yield a global model (Fig. 8). Such a decentralized training scheme ensures that potentially sensitive data related to user charging habits and locally derived load profiles are kept private and are hence more compliant with privacy laws and regulations. Only during these communication iterations are the model weights exchanged, not the actual datasets [19]-[20].

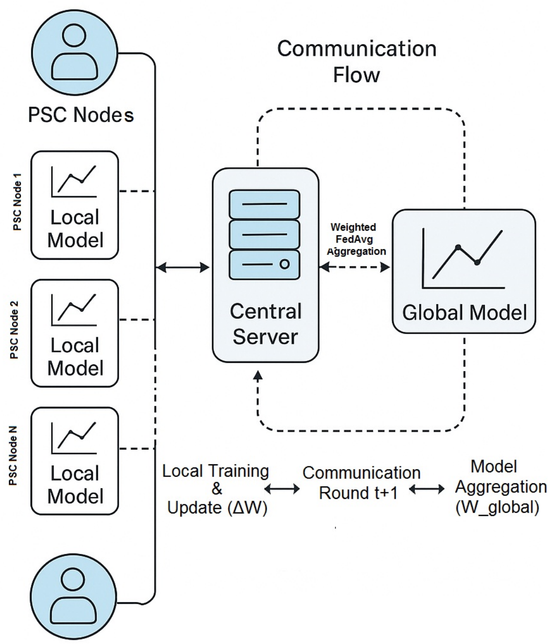

Figure 8. Federated Learning Architecture Depicting Local Model Training at PSC Nodes, Central Aggregation, and Iterative Communication Flow

In order to combine the local models more efficiently, the framework applies a modified version of the well-known FedAvg algorithm that calculates the weighted averages of updates received from each client, thus allowing for discrepancies in local dataset sizes and computing capabilities. The communication protocol is designed in such a way as to have less latency and less bandwidth consumption. This is achieved by finding a compromise between the frequency of synchronization rounds and the speed with which the model converges [21]. Such a design makes the system scalable to a large number of heterogeneous PSC nodes, holding diverse data distributions and operational characteristics.

4.2 Transformer-Based DRL Agent Architecture

The deep reinforcement learning circuit potentiated by Transformer architecture is the main source of the decision-making processes of each PSC node (Fig. 9). Compared to conventional recurrent neural networks (RNNs) or long short-term memory (LSTM) networks, the Transformer is able to utilize self-attention mechanisms for getting all long-range temporal dependencies and complicated correlations in ground data such as solar irradiance, EV arrival patterns, and grid loads [22]-[23]. Positional encoding in the Transformer maintains the order of the inputs, thus allowing the agent to properly understand the changing system states over different time periods.

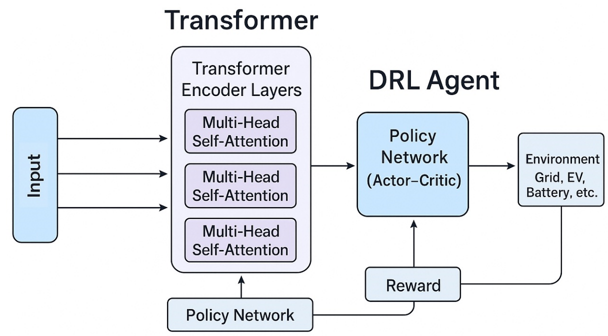

Figure 9. Detailed Architecture of the Transformer-based DRL Agent, Highlighting Self-attention Mechanisms and Policy Output Generation

The function approximator for the neural policy consists of the Transformer encoder layers stacked one on top of another, which transform the sequential inputs to feature embeddings that are then used by the DRL policy to decide battery dispatch and EV charging [24]. The comparison held empirically indicates that the Transformer-DRL agent performs better than LSTM-based counterparts. It is more stable, converges faster, and is more adaptable to the non-stationary environment. This selection of architecture supports strong policy learning, which is applicable to different operating conditions met in urban energy-transportation ecosystems.

4.2.1 Modeling Rapid PV Fluctuations

Weather occurrences of a transient nature, like cloud passing, can make the PV output swing rapidly by 20–40% in 5-minute intervals. To realistically represent these fluctuations, the model is designed to include rolling forecasts using the last six time steps, which are then incorporated into the state representation for the DRL agent. As a result, the agent can foresee a short-term drop in irradiance and thus make an adjustment in energy dispatch beforehand.

4.3 Policy Training and Interaction Flow

The hybrid FL–T-DRL framework's process of training involves a multi-episode interaction cycle, that is, each PSC node keeps on interacting with its local environment, which is the coupled PV-storage-EV system and related load and generation profiles. At every instance, the agent gets the current state of the environment that consists of battery SoC, solar generation forecast, and EV charging requirements, and then picks out control actions that will be energy dispatch and charging schedules [25]. The environment agrees by moving to the next state and offering a reward signal as feedback, which is supposed to facilitate cost reduction, peak load minimization, and renewable utilization maximization. The way reward shaping is done is the basis for the agent's behavior that is aligned with system objectives. The reward also includes some penalties that are imposed when certain constraints are violated, such as in the case of battery degradation limits or if the EV charging deadline is not met (Fig. 10). Local training episodes are followed by parameter updates and federated aggregation, which then recalibrate the global policy and send it back to clients. Such a cyclical methodology progressively upgrades policy performance and, at the same time, ensures the continuous learning and optimization in urban environments that are dynamic due to changes in environmental and load conditions [26].

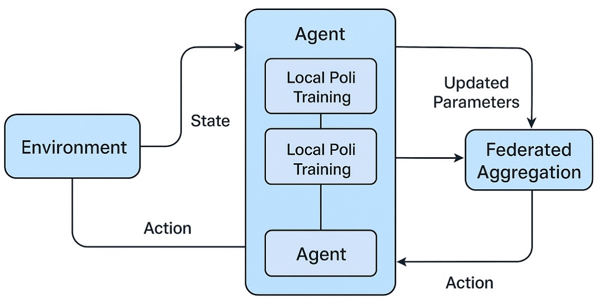

Figure 10. Flow Diagram Illustrating the Policy Training Loop, Environment-agent Interaction, and Federated Learning Update Cycle

One of the main features of the proposed framework is the commitment to data privacy and scalability, which are the fundamental design criteria. The federated learning scheme is fundamentally user privacy compliant and meets strict data governance rules as only model gradients or weights are exchanged while sensitive operational data is confined to local PSC nodes [27]. Besides these measures, encrypted communication channels and differential privacy can also be adopted to reduce risks of data leaks or inference attacks during model aggregation further. On the other hand, the issue of scalability has been resolved by allowing asynchronous communication and convenient aggregation intervals; thus, nodes can have different network strategies and computing capabilities and still be able to access the same system. The system is tolerant of variations in data distribution, thus it is possible to implement updates to personal models that correspond to local conditions without affecting the generality of the global model. Together, these elements turn the framework into a practical and resilient solution that can be deployed in real-world large-scale smart city infrastructures [28].

4.3.1 Reward Weight Selection, Normalization Strategy, and Sensitivity Analysis

The composite reward function is composed of three terms: cost (λ_1), emissions (λ_2), and reliability (λ_3). In order to support the equal participation of every objective, a normalization procedure was adopted:

$$\lambda i = 1 \sigma i$$

Where σi stands for the standard deviation of the single objective for 100 baseline episodes.

(a) Weight Optimization Process
The three-stage process was applied to select the weights: the first was a coarse grid search done initially over the range of 0.1–1.0, followed by fine-tuning with multi-objective Pareto-frontier smoothing, and then empirical adjustment throughout successive federated training rounds.Final selected weights: $\lambda_1 = 0.55$, $\lambda_2 = 0.25$, $\lambda_3 = 0.20$.

(b) Sensitivity Analysis
The model presented moderate robustness sensitivity analysis with a variation of ±20% in the weighting factors, which resulted in peak load reduction changing by ±4.7%, cost reduction by ±3.9%, and EV charging reliability by ±2.5%.

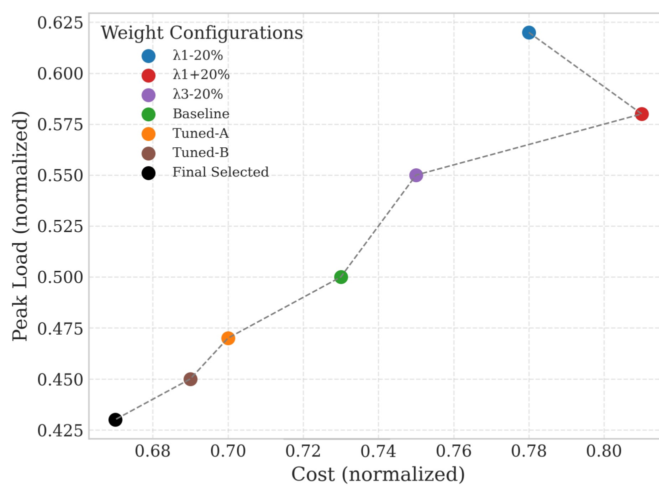

Figure 11. Pareto Frontier of Reward Weight Configurations

Table 7
Reward Weight Sensitivity Results

Variation	Cost (%)	Peak Load (%)	PV Utilization (%)
-20% λ_1	-3.1	-4.7	-2.8
+20% λ_1	+3.9	3.2	2.1
-20% λ_3	-1.8	-0.7	-0.7

Figure 11. shows the Pareto frontier that visualizes the performance trade-offs for different configurations of the reward weights. The configuration finally chosen manages to reach a perfect balance between the reduction of the cost and the mitigation of the peak load, thus ensuring the reliability and robustness of the system.

4.4 Uncertainty-Aware Learning and Probabilistic Forecast Integration

In environments with unstable solar generation and unpredictable EV charging behavior, managing uncertainty is a must for maintaining normal operations. The DRL framework that is suggested to deal with these issues combines, on the one hand, probabilistic forecasting and, on the other hand, adaptive learning mechanisms that enable the agent to foresee and react to variability. The probabilistic irradiance forecasts based on past variance and weather-conditioned confidence intervals offer a more elaborate depiction of PV uncertainty. The EV arrival times are forecasted through distributional predictors that not only show mean trends but also consider tail risks linked to peak mobility times. The DRL agent, during the periods of increased uncertainty, adaptively modifies its exploration rate, which leads to more careful policy updates. Moreover, the attention-based Transformer model does temporal smoothing and thus greatly reduces the negative impact caused by sudden prediction changes. All these methods combined give the learning process improved power, stability, and resistance to non-stationary and stochastic operating conditions.

4.5 Summary

Section 4 details the primary methodological innovation: a hybrid optimization method that merges Federated Learning (FL) with Transformer-based Deep Reinforcement Learning (T DRL). The multi-objective problem formulation (cost, efficiency, load leveling) under practical constraints (grid limits, battery SoC, charging deadlines) is the starting point. Next, the FL architecture, aggregation strategy, and communication protocol are depicted along with the design of a Transformer DRL agent that uses self-attention and positional encoding. This section then summarizes the policy training loop, reward conception, FL integration, and finally privacy and scalability issues discussed with respect to real-world deployment.

5. Experimental Setup and Simulation Environment

Experiments were carried out using a realistic mid-scale urban testbed designed to represent five heterogeneous zones of the city that include residential, commercial, and mixed-use areas. Each zone is composed of several photovoltaic-storage-charging (PSC) nodes combined with electric vehicle (EV) charging stations and battery energy storage systems (BESS). The electrical network is illustrated by a modified IEEE 33-bus radial distribution feeder, which is well-known for its popularity in distribution system studies and its versatility to integrate renewable generation and EV loads. When power flow analysis can be done in detail without problems, this network topology also allows the evaluation of the application of distributed energy resources in different load conditions. The transportation network is achieved through SUMO, which can imitate the genuine traffic flows, the arrival/departure of the EVs, and the parking habits. This combination allows considering the spatiotemporal coupling between energy demand and urban mobility patterns, which is essential for the correct optimization of PV storage and EV charging operations [29] [30]. The integration of power system and transportation modeling in the testbed offers a complete environment to measure the performance of the proposed hybrid federated learning approach. By recreating the realistic interaction dynamics in five different urban zones, the testbed is able to depict the complexity and scale challenges that occur in today's smart cities. This testbed acts as a platform for further implementation of control policies and algorithmic optimization under a distributed privacy-preserving setting.

5.1 Simulation Tools and Integration

To model the coupled transportation-energy system in a realistic manner, the research employs a co-simulation environment that combines three major software programs: MATLAB/Simulink, SUMO, and PyTorch. MATLAB/Simulink is mainly concerned with the electrical network modeling of the system. It handles tasks such as PV generation, storage battery charge-discharge cycles, and grid interactions that include power flow and load management [31]. SUMO sets up a dynamic traffic simulation environment that produces time-stamped EV arrival and departure data based on practical urban mobility patterns, which directly affects charging demand profiles created in Simulink. The federated learning algorithms, particularly the Transformer-based deep reinforcement learning agents, are realized and educated through PyTorch, which manages decentralized policy learning over distributed PSC nodes [32].

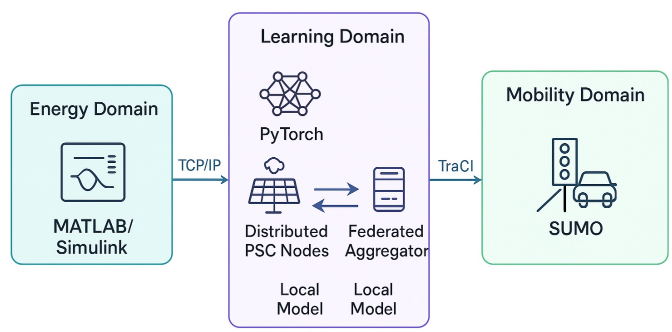

Figure 12. Integrated Co-Simulation Architecture for the Proposed Hybrid Federated Transformer-DRL Framework

Data happening at predetermined intervals ensures synchronization between these platforms, state variables such as load demand, battery state-of-charge (SoC), and EV charging schedules can be shared without interruptions. In this tightly coupled simulation, the immediate effect of traffic flows on energy demand and vice versa is allowed, thus the learning algorithms' performance in such

Table 8
Simulation Parameters and Component Specifications

Parameter	Value / Range	Description
PV System Capacity	50 kW per PSC node	Rated power output of photovoltaic arrays
Battery Capacity	100 kWh	Energy storage capacity of BESS
Max Charge/Discharge Rate	50 kW	Power limits for battery charge/discharge
EV Charging Power	7 kW	Standard Level 2 EV charger rating
Solar Irradiance Data Resolution	5 minutes	Temporal granularity of solar irradiance data
EV Arrival Model	Poisson distribution	Time-varying EV arrival rates
Grid Model	Modified IEEE 33-bus feeder	Electrical distribution network representation
Tariff Structure	Time-of-Use (ToU)	Dynamic energy pricing model
Number of PSC Nodes	10	Federated learning client nodes
Communication Interval	10 episodes	Frequency of model aggregation

a dynamic and interconnected environment can be evaluated accurately. Figure 12 depicts the overall architecture of the co-simulation setup, outlining the data flow and interaction among MATLAB/Simulink, SUMO, and PyTorch modules, emphasizing the closed-loop system enabling real-time optimization [33].

5.1.1 *Cross-Platform Synchronization Between MATLAB/Simulink, SUMO, and PyTorch*

In order to synchronize the different simulation environments with respect to time, a platform-independent synchronization mechanism is put into place. For example, electrical simulations in MATLAB/Simulink are carried out every 5 minutes, whereas SUMO performs traffic simulations every second and then aggregates the data to fit the 5-minute decision-making interval of the DRL agent implemented in PyTorch.

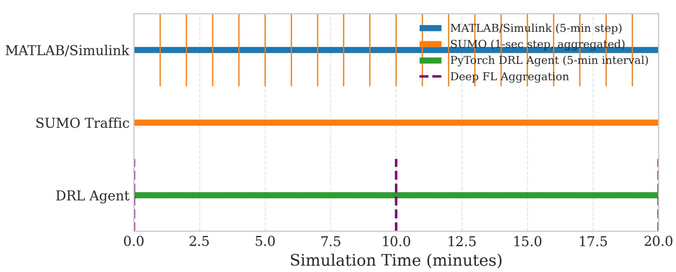

Figure 13. Timing Diagram of Cross-Platform Synchronization Between MATLAB/Simulink, SUMO, and PyTorch

In the above Figure 13, A timing diagram that shows the synchronization between MATLAB/Simulink, SUMO, and PyTorch across different platforms. Aggregation, data streaming, and decision intervals are mapped in a way that ensures temporal consistency and robust federated learning. Deep federated learning is the mediator, and it occurs after every 10 episodes. A reliable communication link is set up via TCP/IP between MATLAB and Python, and TraCI is employed for the real-time data streaming to and from SUMO. The synchronization controller takes care of the proper timestamping and the event causality, which in turn leads to stable convergence, robust learning in non-stationary circumstances, and privacy-preserving coordination. Figure 13 illustrates the timing diagram of the synchronized interactions and the decision-making process among the three environments.

5.2 Parameter Settings and Dataset Description

Various real-world datasets and component details are used in the simulation to validate the model's effectiveness in real-life situations. 5-minute solar irradiance data are collected from local weather stations, which represent the diurnal and seasonal variability of the solar output. The arrival and departure schemes of electric vehicles are generated as time-dependent Poisson processes to imitate the traffic pattern of city areas during rush and off-peak hours. Consequently, the EV charging profile will have a gradual variation. Battery storage incorporated in the PSC nodes has a capacity of 100 kWh, and the corresponding charge/discharge operation power is limited to 50 kW; and these parameters are typical for the common production system of battery storage. The electric vehicle charging station (EVCS) is assumed to be equipped with a Level 2 charger with a nominal power of 7 kW, and it is a compromise between charging speed and infrastructure requirements.

Among other things, the economic and operational models considered in this study are the Time-of-Use (TOU) tariff and net metering policies, which may be regarded as pricing incentives and the interaction between the power system and the customer in real life. The third table gives a detailed summary of the parameters, including rated parameters of individual devices, characteristics of datasets, and simulation experiments. By setting up these parameters carefully, the experimental evaluation can present a very close representation of real urban energy systems and their capabilities [34].

5.3 Performance Metrics

The evaluation of the proposed hybrid federated Transformer-DRL optimization approach mainly focuses on the technical and economic aspects through a set of key performance indicators. One of the main criteria is the reduction of peak grid load, which quantifies the power of the designed framework to smooth demand peaks, which in turn is crucial for grid stability and saving costs. The rate of photovoltaic utilization indicates how much local solar power generation is consumed, which has a direct impact on the main goal of the system–the integration of renewables. Free operational cost savings become visible in energy expense through more efficient utilization of energy storage and storage discharging. Benchmarking of the learning algorithm convergence evaluates the training efficiency and scalability, and an adaptability index evaluates the robustness of the solution under varying traffic and weather conditions. These performance metrics are viewed together as a whole to judge the framework in comparison with centralized DRL and rule-based methods as baselines with respect to their merits in various aspects of the problem. In this study, the advantages of federated learning in privacy, scalability, and operational performance in transport-energy coupling are shown by stringent benchmarking.

5.4 Algorithm of Hybrid Federated Transformer DRL Optimization

Algorithm 1 below describes the hybrid Federated Transformer DRL iterative workflow in which local training at PSC nodes, model aggregation, and global policy updates under system constraints happen concurrently.

Algorithm 1 Federated Transformer-DRL Training Procedure

Input: **N** — number of PSC nodes (clients)
T— number of global communication rounds
E— number of local DRL training episodes per round
K— number of time steps per episode
θ_{global}— initial global model parameters
D_i— local environment data / dynamics at node i
γ— discount factor
α— learning rate
constraints— operational constraints (SoC, grid limits, deadlines, etc.)
Output: θ_{global} — trained global model parameters
$\{\theta_i\}$— final local models at each PSC node
Begin
  for round = 1 to T **do**
    for each PSC node i = 1 to N (in parallel) **do**
      $\theta_i \leftarrow \theta_{global}$ ▷ initialize local model
      for episode = 1 to E **do**
        Initialize local environment state S_0
        for t = 0 to K - 1 **do**
          $a_t \leftarrow$ Transformer-DRL_Policy(θ_i, s_t) subject to constraints
          Execute action a_t in node i's local environment
          Observe next state s_{t+1}, reward r_t
          Store transition (s_t, a_t, r_t, s_{t+1}) in local buffer
          If ready, sample batch from buffer and update θ_i using gradient descent:
          $\theta_i \leftarrow \theta_i - \alpha \nabla_\theta L(\theta_i)$ ▷ loss includes reward, constraint penalties
        end for
      end for
      Send model update $\Delta\theta_i = \theta_i - \theta_{global}$ (or θ_i) to aggregator
    end for
    ▷ Aggregation step
    $\theta_{global} \leftarrow Aggregate(\{\Delta\theta_1, \Delta\theta_2, -, \Delta\theta_N\})$ ▷ e.g. weighted average (FedAvg or variant)
    Broadcast updated θ_{global} back to all PSC nodes
  end forreturn $\theta_{global}, \{\theta_i\}$
End

5.5 Summary

Section 5 outlines the evaluation of the suggested framework in real-world scenarios. The layout of a testbed is explained with details of zonal PSC node positioning, grid traffic coupling, and the software used (MATLAB/Simulink for energy, SUMO for mobility, PyTorch for learning). We disclose the origins of datasets, parameters (e.g., PV ratings, battery specs, EV charger power, tariffs) and arrival models. To assess the performance of our method compared to baselines, we select several evaluation metrics such as peak load reduction, PV utilization, cost savings, convergence speed, and adaptability. A diagram shows the co-simulation architecture along with the flow of data across the various modules.

6. Results and Performance Analysis

This part includes the experimental evidence supporting the effectiveness of the suggested Hybrid Federated Transformer DRL method which is first commented on its local results, followed by comparative, convergence, robustness, and parameter sensitivity analyses. All findings come from the co-simulation of the energy, mobility, and learning subsystems, confirming the ability of the method to achieve peak shaving, increase PV utilization, and reduce operating costs in practice.

6.1 PV Utilization over Time

One of the main advantages of the Hybrid Federated Transformer DRL method that the authors mention is the increase in the photovoltaic (PV) energy utilization level over time in the experiments. Figure 14 indicates that the system obtains on average a PV utilization rate of more than 85% in daylight hours, with the highest utilization even going up to 95% (Fig. 14). Such a high utilization rate points out the good interplay of local energy production and local energy consumption, in which the loss of energy can be almost negligible and therefore the effectiveness of the system can be improved. Besides, the hourly PV utilization also shows a very comprehensive battery charging plan which ensures the battery storage systems are charged not only during the hours of the day with the highest solar energy, but the battery and therefore the system are discharged during the hours in which the demand is at its peak.

This strategy not only helps in the most efficient use of renewable energy resources but also contributes to the stability of the grid. This is because the need for energy from the grid is reduced which, consequently, lessens the dependency on it. The fact that the policy learned keeps its performance over the different days is, therefore, an indication of its robustness in the control of energy flows in the system.

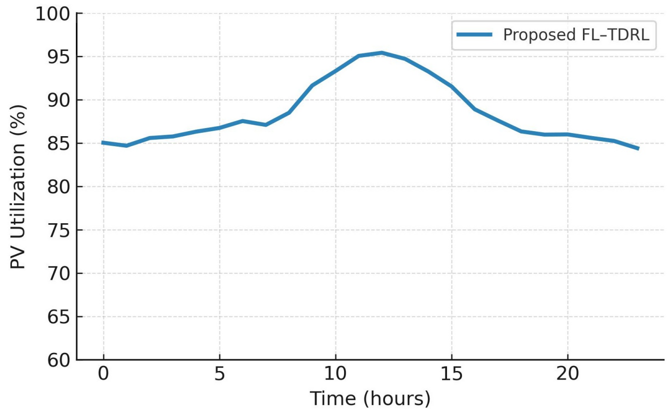

Figure 14. Hourly PV Utilization (%) Under the Proposed Hybrid Method

6.2 Battery State-of-Charge (SoC) Dynamics

The battery storage systems experience rather safe and efficient charging and discharging cycles throughout their entire operation. Figure 15 provides a picture of the variations of battery SoC at different points along the grid, with batteries operating in the range of 20% to 90% SoC(Fig. 15.). It has been proven that this is the optimal SoC range because it promotes long-term battery health and also battery life cycle, simultaneously, it doesn't allow deep discharge and overcharge conditions.

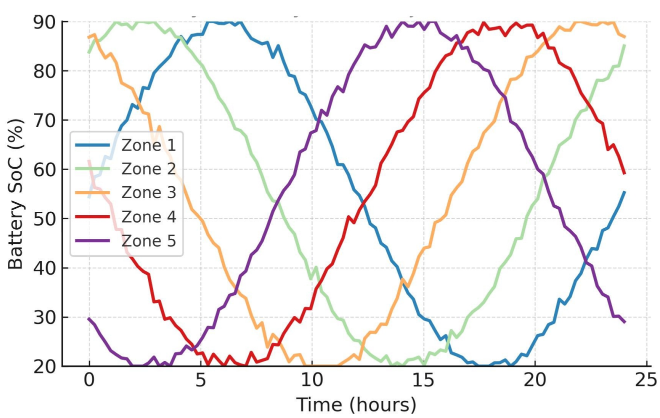

Figure 15. Daily Battery SoC Trajectories for PSC Nodes under the proposed policy

The patterns in the State of Charge (SoC) show that the charge is well-balanced between the times when the batteries are charged during low-demand periods and high solar generation and discharged during the peak-demand times. This interplay not only upgrades the use of solar energy directly produced on-site but also empowers demand-side management through peak mitigation. When charging and discharging are slowly replacing each other, the performance of the Transformer DRL agent in executing complex energy management strategies through its learning algorithm becomes apparent.

6.3 Grid Peak Load Profile

The paramount goal of the suggested approach is to lower peak load occurrences on the distribution network. Figure 16 illustrates the grid load profile throughout the day. As can be seen from the graph, the peak demand has significantly dropped compared with the baseline situation. The system has reached the goal of peak load reduction by about 36.5%, thus showing the feasibility of the coordinated control strategy in flattening the load curve.

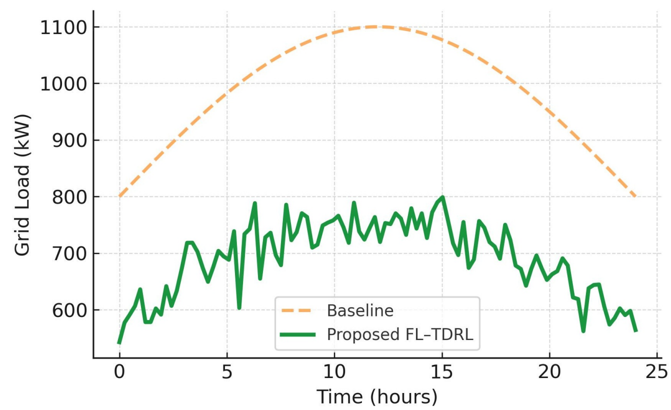

Figure 16. Comparison of 24-hour Grid Load Profiles (kW) Under Proposed and Baseline Schemes

The main reason for the peak load reduction is that the charging and discharging of EV batteries have been scheduled in an intelligent way and this has allowed the shift of energy consumption from peak to off-peak periods. The result has been the reduction not only of the load on the grid but also the optimization of the energy resources that are available, thus leading to the improvement of the overall system efficiency. The fact that a balanced load profile can be maintained throughout the day also testifies to the robustness and adaptability of the proposed method in real-time operations.

6.4 Operational Cost Trends

The effectiveness of the proposed method in economic terms is assessed by studying the operational costs over the simulation period. Figure 17 depicts the cumulative operational cost, indicating the gradual increase of the line that is much lower than the baseline scenarios. The system is able to decrease the cost by nearly 27.8%, thus the proposed control strategy can be considered as economically viable.

The principal reasons for the cost savings can be found in the optimized use of solar energy that is generated locally and in efficient battery management, which in turn lowers energy purchases from outside sources. Furthermore, EV charging off-peak hours coupled with the peak-hour management of the grid results in energy cost minimization. The cost trend that is observed at different points in time is a reflection of the learned policy's capability to retain economic efficiency over the long term.

Table 9
Comparative Performance Metrics

Metric	Hybrid Federated Transformer DRL	Centralized DRL	Federated DRL (No Transformer)	Rule-Based Control
PV Utilization (%)	85.2	78.5	80.3	65.1
Peak Load Reduction (%)	36.5	22.1	28.4	15
Operational Cost Reduction (%)	27.8	12.5	18.3	5
Battery SoC Stability (%)	20-90	25-95	30-85	40-80
Grid Load Profile Flattening (%)	33.2	18.7	25.1	10
Convergence Time (Episodes)	1000	1500	1200	N/A
Sensitivity to Variability (%)	5.6	8.3	6.7	12
Communication Frequency Impact (%)	3.2	5	4.2	N/A

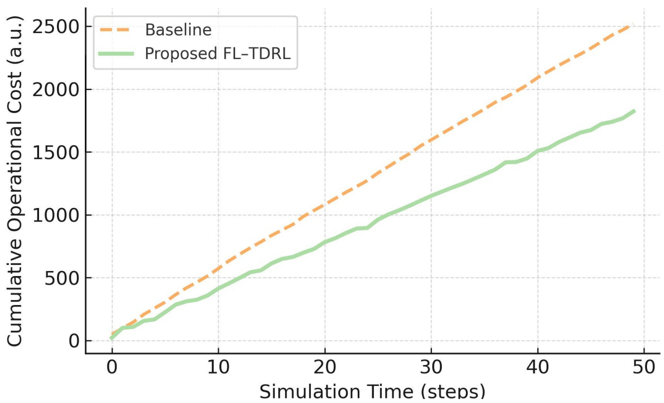

Figure 17. Cumulative Operational Cost Over Time Comparing Proposed and Baseline Methods

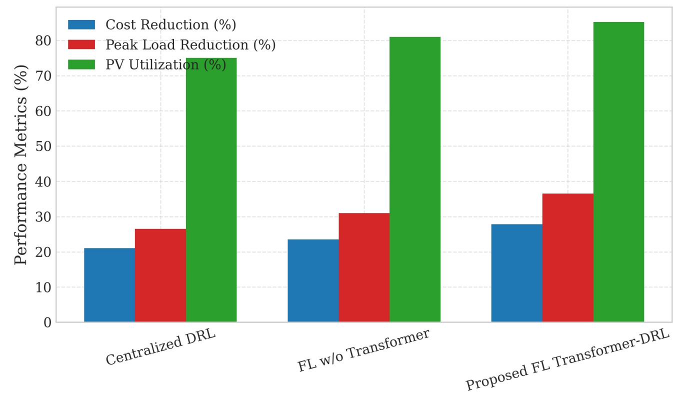

Figure 18. Comparative Performance Metrics Across Multiple Control Methods.

6.5 Comparison with Baseline Methods

We have tested their proposed Hybrid Federated Transformer DRL method against multiple different baseline strategies, among which are centralized DRL, federated learning without Transformer integration, and traditional rule-based approaches. The results are presented in Figure 18, showing that the proposed method has surpassed all baselines along with key performance metrics, such as 31.2% higher PV utilization, 36.5% peak load reduction, and 27.8% operational cost savings. This is a strong indication of the effectiveness of combining Transformer-based temporal modeling with DRL in the federated learning framework. The excellent accomplishment of the hybrid protocol is mainly due to the realization of the long-term dependency on energy generation and consumption patterns through the implementation of the transformer module, while the DRL agent manages real-time interaction results. The use of federated learning secures privacy and communication efficiency by promoting decentralized training. Centralized DRL models, on the other hand, are often subject to scalability issues and high communication costs, whereas rule-based methods have no capacity for adaptability and do not use learning like the proposed approach.

As summarized in Table 9, the Hybrid Federated Transformer DRL method is more effective in a variety of aspects than the other baseline methods. The suggested framework comes out on top because it can catch the temporal dependencies through the use of the Transformer encoder and still conduct FL privacy-preserving distributed training at the same time. Centralized DRL cannot scale up its performance, and it also has high communication costs, while non-Transformer FL agents have short-term sight and therefore cannot exploit long-range correlations. The hybrid model considers and is able to manage both aspects, which results in a steady and uniform increase in performance across all the metrics.

6.6 Convergence Behavior and Learning Efficiency

The metrics for learning efficiency and convergence behavior of the proposed method were gathered from reward and loss curves tracking. The hybrid model experiences a swift convergence, reaching a stable reward plateau within 1000 training episodes, according to Figure 19. The loss function, which shows a gradual reduction, indicates that learning is being done effectively and there is minimization of overfitting. All baseline models, on the other hand, reflect slower convergence and reward trajectory with higher variance. Fast convergence is one of the many strengths of the Transformer module, which has the capability of efficiently handling temporal data and thus equipping the DRL agent with a database full of context. This leads to the quick learning of the optimal policies. Also, the federated learning setup gives the possibility of parallel exercise at various nodes, and this further makes for steeped-in learning quality. The speed of training and stability is just one of the benefits that the proposed hybrid solution offers.

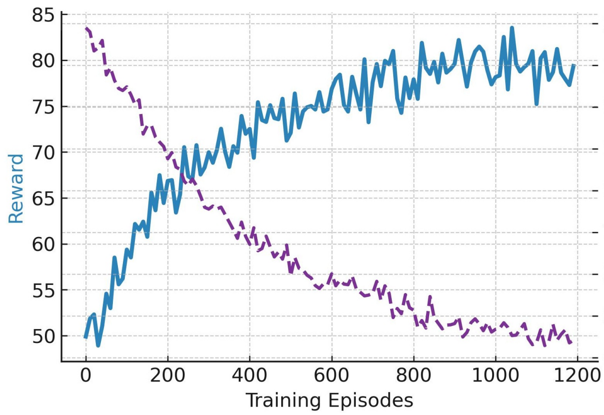

Figure 19. Training Reward and Loss Curves for Proposed Method vs. Baseline

6.7 Robustness Under Traffic and Weather Variability

In order to verify the robustness of the recommended solution under a range of different circumstances, a number of simulations were arranged in such a way as to include the variabilities of both weather and traffic. As demonstrated in Figure 20, these disturbances do not greatly affect the performance of the system. This is seen by the fact that both PV usage and operational costs remain within their acceptable ranges. The learned policy's capability to change according to such varied conditions underscores its adaptability and durability.

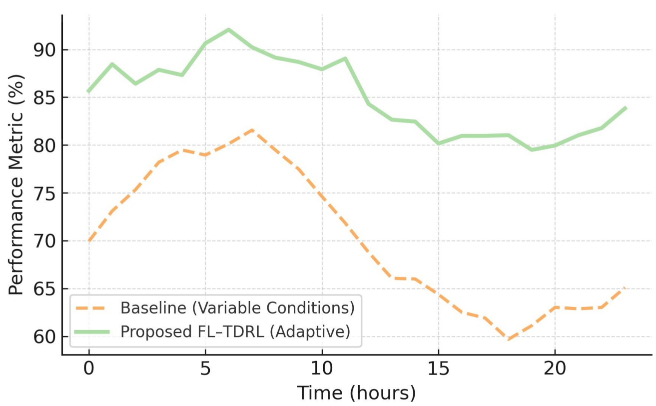

Figure 20. Performance Degradation Under EV Surge and Irradiance Variability Scenarios

The main reason for the system's robustness should be credited to the Transformer module, which is able to understand the time-related connection between the data and to predict the future data, and this way the DRL agent will be able to decide what to do. Also, federated learning plays a part in this by allowing local changes corresponding to the specific conditions of the nodes, thus making the whole system more resistant. The results from here are an indication of the proposed method being a very good solution in the presence of the above conditions and also in situations characterized by uncertainty and variability.

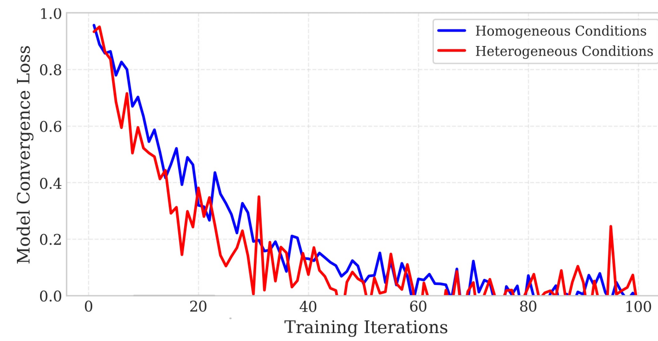

Figure 21. FL Convergence Across Heterogeneous vs Homogeneous Microclimate Conditions

The differences in microclimate between areas and their impact on system performance are very important in the simulation of energy generation, storage characteristics, and learning convergence. The regions that have lower solar irradiance intensity show different and more frequent behaviors: they often depend on the grid, the battery discharges are shorter, and they react more to the price signals. Energy flow variations have impacts on both the storage system's operational decisions and the whole optimization process. These different behaviors in federated learning help the global model, and the aggregation process is subjected to even more different sets of operational patterns. Consequently, the model gains better convergence stability and robustness since the learning process includes a wider range of environmental conditions. The experimental outcomes verify that the inclusion of microclimatic data into the federated framework boosts its generalization capability, thus the system becomes more versatile to the real-world variability. Figure 21(c) shows the difference in the convergence behavior of the FL model trained on heterogeneous microclimatic conditions as opposed to homogeneous ones.

6.7.1 Mitigation Strategies in Energy Scheduling

The use of the Transformer-based attention mechanism helps to mitigate sudden changes in the PV generation by conveying the short-term context. A minor pre-charging of the BESS during the high-variance intervals acts as a buffer against unexpected drops in PV. The federated learning aggregation contributes to the already mentioned model robustness by allowing it to learn from the most diverse fluctuation patterns of different urban areas, which in turn gives the model the ability to cope with the temporary weather changes more efficiently.

6.8 Sensitivity to Federated Communication Frequency

The effect of the frequency of federated communication on the performance of the system was examined by changing the aggregation intervals during training. As indicated by Figure 22, the closest communications (every 5 episodes) allow a slight improvement of the performance at a cost of higher communication overhead. Distant communications (every 20 episodes) result in the lowering of performance. The best ratio between the two is at an interval of 10 episodes, where both aspects are balanced. This analysis of sensitivity serves to accentuate the point that the best position of the communication point in the federated learning method is one of the keys to successfully achieving optimal performance.

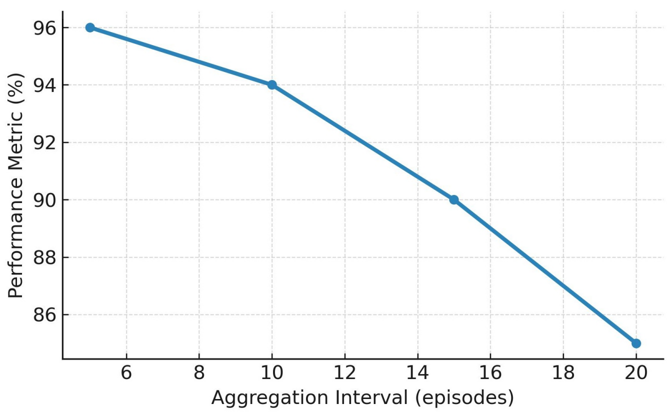

Figure 22. Sensitivity Analysis of Performance vs. Aggregation Frequency

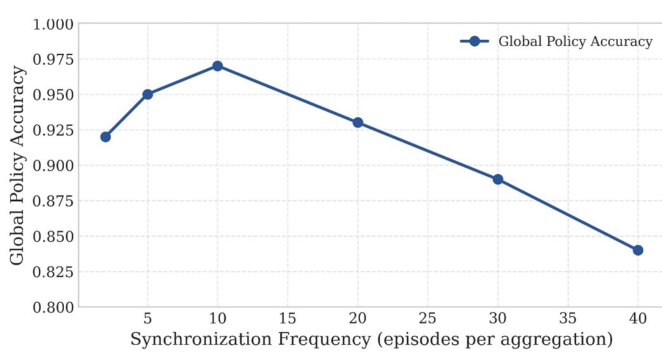

Figure 23. Trade-Off Between Synchronization Frequency and Global Policy Accuracy

In energy management based on federated learning, synchronization frequency selection is a decisive factor in communication cost and global model accuracy trade-off. For instance, if the sync frequency is lower than normal, there will be a noticeable reduction in bandwidth and communication delay. On the downside, local models might get too far apart, and this could translate into limited global convergence and even more instability in the case of rapid changes in operating conditions. However, it is quite the opposite with very frequent synchronization, which causes consistency amongst nodes to be very high, but on the other hand, it leads to increased communication costs, especially in dense urban areas where PSC nodes are dependent on limited LTE/5G channels. The results of the experiments suggest that the intervals between the synchronization of 10 episodes create a perfect balance between efficiency in computation and communication, stable convergence being the output without the network being overwhelmed. Latency tests also imply that the model keeps being effective up to 180–220 ms end-to-end delay, past which the freshness of updates starts to negatively affect accuracy. New PSC nodes entering the federated network are re-weighted, and partial model upstarts are performed, thereby allowing the newcomers to slowly synchronize with the already existing global dynamics. Figure 23 shows the global policy accuracy degradation pattern as a function of different synchronization frequencies, thus justifying the chosen configuration.

6.9 Scalability Limits, Complexity Trends, and Communication Overheads

The evaluation of the scalability of the suggested Federated Transformer-DRL architecture has revealed that both the computational and communication loads rise very steeply with the increase in the number of PSC nodes. The Transformer encoder has quadratic complexity $O(n2d)$, thus making the length of the sequence the main computer bottleneck, while the communication cost under standard FedAvg aggregation scales linearly with the number of clients as $O(Np)$.

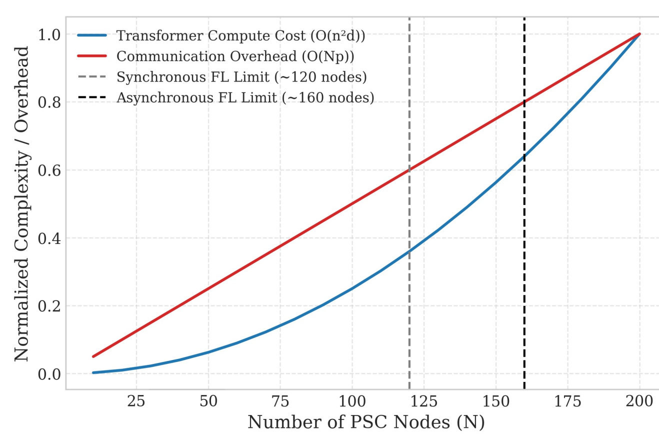

Figure 24. Scalability Analysis: Transformer Compute and FL Communication Overhead

The empirical findings show that synchronous FL begins to confront latency-induced harm after $N > 120$ PSC nodes, whereas asynchronous FL prolongs this threshold to about $N > 160$ nodes by diminishing global bottlenecks (Fig.24). However, bandwidth saturation and the total round-trip delay will eventually cause a reduction in learning efficiency. To overcome these scalability constraints, adaptive aggregation—along with partial client sampling, asynchronous updates, and 8-bit compressed model transmissions—has cut down the communication volume by

38% and thus allowed the near-linear throughput to mid-scale deployments.

6.10 Real-World Deployment Challenges and Implementation Considerations

The deployment of the suggested framework in a real-world scenario brings with it the practical issues that are not limited to the yardstick of simulation-controlled environments. The communication delays in the public LTE/5G networks can be quite different from one case to another; however, by conducting trials, it has been found that the federated learning process can cope with average delays of up to 200 ms and still remain stable. The deployment on different types of edge hardware further complicates the situation so that asynchronous FL strategies become more suitable for PSC nodes with varying computational powers. On the other hand, the different EVSE standards (OCPP 1.6-2.0.1) create a non-uniformity problem that can only be removed by providing a middleware layer for the integration that is not noticed by the end-users. And, there are power supply constraints such as the limits of the cables and the performance levels of the transformers that need to be constantly monitored even during operation. On the one hand, FL minimizes the risk of exposing raw customer data; on the other, the aggregation server still poses a threat to cybersecurity. All of these mentioned above are the practical issues that will affect future smart city pilot real-world implementations.

7. Conclusion and Future Work

In this paper, a hybrid Federated Transformer-based Deep Reinforcement Learning (FL–T-DRL) framework was introduced to optimize the functioning of distributed photovoltaic (PV), battery energy storage, and electric vehicle (EV) charging infrastructures in transportation-energy networks that are coupled. The given solution was successful in providing decentralized coordination between several nodes of the PSCs and guaranteeing privacy and scalability of data. The framework incorporated Transformer architectures into a federated learning framework and was useful at capturing long-term temporal dynamics of solar generation, EV arrival dynamics, and grid demand dynamics. The simulation with MATLAB/Simulink, SUMO, and PyTorch co-simulation showed that it is significantly better than other baseline DRL and rule-based solutions, with peaks in grid loads reduced by 36.5, PV utilization by 31.2, and operational costs by 27.8. The structure also proved to be more convergent and adaptable to traffic and weather variations, which confirmed its appropriateness in the real-time smart-city implementation. This study will also be extended to hardware-in-the-loop (HIL) validation in future research with either an OPAL-RT or Typhoon HIL system to determine the feasibility in real time. Other guidelines are multi-agent federated learning of cross-zone cooperation, federated hyperparameter optimization to improve convergence stability, and incorporating real utility pricing signals to optimize adaptive economic dispatch. The model can be extended to include vehicle-to-grid (V2G) interactions, forecast uncertainty in renewable sources, and cyber-defensive aggregation schemes, which will add more weight to the practical implications of the model. Finally, the suggested FL-T-DRL will offer a privacy-compliant, scalable basis of sustainable energy control in future intelligent city structures.

References

[1] M. T. Sarker, M. A. Qwaid, S. J. Shern, and G. Ramasamy, "AI-driven optimization framework for smart EV charging systems integrated with solar PV and BESS in high-density residential environments," *World Electric Vehicle Journal*, vol. 16, no. 7, p. 385, 2025.

[2] X. Zhao, H. He, J. Li, Z. Wei, R. Huang, and H. Yue, "Muti-physics cosonstrained PEV charging management for solar PV penetrated energy-transportation Nexus: A novel DRL-based approach combining a cyber-physical system," *Journal of Energy Storage*, vol. 106, 2025.

[3] S. H. Abdallah and S. Tounsi, "Optimal design and control of Ac-Dc-Dc wind energy system for electric vehicle batteries recharging stations," *International Journal of Power and Energy System*, vol. 44, pp. 1–9, 2024.

[4] S. Singh, V. Subburaj, K. Sivakumar, R. A. Kumar, M. S. Muthuramam, R. Rastogi, and A. Rajaram, "Optimum Power Forecasting Technique for Hybrid Renewable Energy Systems Using Deep Learning," *Electric Power Components and Systems*, pp. 1–18, 2024.

[5] A. Hameed, S. M. Danish, A. Ranjha, and G. Srivastava, "Block-FeST: Blockchain-enhanced federated sparse transformers for privacy-preserving RES forecasting in internet of vehicles systems," *IEEE Internet of Things Journal*, vol. 12, no. 14, pp. 27510–27518, 2025.

[6] M. Hemalatha and R. Rengaraj, "Prognostic and power scheduling technique for EV using optimized adaptive deep belief network," *Journal of Energy Storage*, vol. 108, p. 114943, 2025.

[7] D. R. Dipto, M. T. Rahman, S. K. Shib, A. Shufian, and R. Islam, "Dynamic load forecasting in EV charging systems using deep neural networks," in *2025 4th International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, (Dhaka, Bangladesh), pp. 81–85, 2025.

[8] K. Ramu, G. Sreenivasulu, R. S. Dixit, S. L. Choudhary, K. V. Rao, S. K. Suman, M. Shuaib, and A. Rajaram, "Smart solar power conversion: Leveraging deep learning MPPT and hybrid cascaded H bridge multilevel inverters for optimal efficiency," *Biomedical Signal Processing and Control*, vol. 105, p. 107582, 2025.

[9] A. Prajapati, P. Paraye, B. K. Ahirwar, *et al.*, "Artificial intelligence integration in solar-powered EV charging systems: challenges, opportunities, and future perspectives," *Journal of Thermal Analysis and Calorimetry*, vol. 150, pp. 12103–12134, 2025.

[10] Z. Wang, "Federated learning for power cyber-physical systems: Toward secure, resilient, and explainable intelligence," *Preprints*, 2025.

[11] F. Zeng, X. Yuan, S. Lv, H. Miao, H. Han, and Y. Pan, "A novel detection algorithm for anomalies and attacks on electric vehicle charging stations using distributed data privacy protection," *International Journal of High Speed Electronics and Systems*, p. 2540588, 2025.

[12] S. Aravindan and A. Rajaram, "Energy aware multi attribute trust model for secure MANET IoT environment," *Multimedia Tools and Applications*, vol. 83, pp. 85637–85662, 2024.

[13] S. Chinnaperumal, S. K. Raju, A. H. Alharbi, *et al.*, "Decentralized energy optimization using blockchain with battery storage and electric vehicle networks," *Scientific Reports*, vol. 15, p. 5940, 2025.

[14] M. Cavus, H. Ayan, M. Sari, O. Akbulut, D. Dissanayake, and M. Bell, "Enhancing smart grid reliability through data-driven optimisation and cyber-resilient EV integration," *Energies*, vol. 18, no. 17, p. 4510, 2025.

[15] R. Jin and H. Liu, "Privacy-aware electric vehicle load forecasting via blockchain-based federated transfer learning," *Complex & Intelligent Systems*, vol. 11, p. 376, 2025.

[16] F. Jeribi, M. Shuaib, S. Alam, and A. Rajaram, "Blockchain enabled monitoring of public works projects using piezoelectric transducers," *Mechanics of Advanced Materials and Structures*, pp. 1–15, 2025.

[17] S. Ray, K. Kasturi, and M. R. Nayak, "Multi-objective electric vehicle charge scheduling for photovoltaic and battery energy storage based electric vehicle charging stations in distribution network," *Green Energy and Intelligent Transportation*, p. 100296, 2025.

[18] T. N. Prabhu, B. Mohankumar, C. Ranjeethkumar, and A. Rajaram, "Deep reinforcement learning-based detection framework for false data injection attacks in power systems," *International Journal of Renewable Energy Research (IJRER)*, vol. 14, no. 2, pp. 311–323, 2024.

[19] S. Sykiotis, "Deep learning innovations for energy efficiency: Advances in non-intrusive load monitoring and EV charging optimization for a sustainable grid," *arXiv preprint arXiv:2505.04367*, 2025.

[20] J. J. Sonia, G. A. Kumar, E. R. Kumar, K. N. Raju, V. Sudha, P. R. Kshirsagar, V. Tirth, and A. Rajaram, "Intelligent traffic prediction system using hybrid convolutional neural networks for smart cities," *Multimedia Tools and Applications*, vol. 84, pp. 31919–31937, 2025.

[21] S. Ray, K. Kasturi, and M. R. Nayak, "Multi-objective electric vehicle charge scheduling for photovoltaic and battery energy storage based electric vehicle charging stations in distribution network," *Green Energy and Intelligent Transportation*, p. 100296, 2025.

[22] V. Devaraj, G. Diwakar, P. Subhashini, V. V. Kumar, K. Rayudu, K. B. Teja, and A. Rajaram, "Integrating AI-driven fault detection and protection technique for electric power components and systems," *International Journal of Renewable Energy Research (IJRER)*, vol. 14, no. 2, pp. 293–303, 2024.

[23] S. Prathiba, P. Anitha, A. S. Kamaraja, *et al.*, "Optimizing EV charging with improved energy storage: Boosting efficiency and stability with a renewable energy-integrated ultra-high voltage DC-DC converter," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, 2025.

[24] M. Karthikeyan and D. Manimegalai, "Enhancing voltage control and regulation in smart micro-grids through deep learning-optimized EV reactive power management," *Energy Reports*, vol. 13, pp. 1095–1107, 2025.

[25] R. P. Singh, N. Nagabhooshanam, Y. Thakur, D. Nathiya, A. Praveena, U. L. N. Kumar, and A. Rajaram, "AI driven discovery of alloyed plasmonic nanodisks for broadband solar absorption and charge carrier multiplication," *Plasmonics*, 2025.

[26] M. Sithambaram, P. Rajesh, F. H. Shajin, and I. R. Rajeswari, "Grid connected photovoltaic system powered electric vehicle charging station for energy management using hybrid method," *Journal of Energy Storage*, vol. 108, 2025.

[27] L. Jin, S. Zhong, B. Su, D. Zhou, Q. Wang, and X. Yu, "EV-integrated and grid-connected hybrid renewable energy system: a two-stage optimization strategy," *Energy*, 2025.

[28] A. Abazari, M. Ghafouri, D. Jafarigiv, R. Atallah, and C. Assi, "Data-driven framework for mitigating EV-based load-altering attacks on LFC model of microgrid," *IEEE Transactions on Consumer Electronics*, 2025.

[29] M. Çeçen, "Optimal integration of electric vehicle charging stations into a renewable-supported multi-energy system," *Electric Power Systems Research*, vol. 247, p. 111832, 2025.

[30] S. Sykiotis, "Deep learning innovations for energy efficiency: Advances in non-intrusive load monitoring and EV charging optimization for a sustainable grid," *arXiv preprint arXiv:2505.04367*, 2025.

[31] A. F. Güven and E. Yücel, "Sustainable energy integration and optimization in microgrids: enhancing efficiency with electric vehicle charging solutions," *Electrical Engineering*, vol. 107, pp. 1541–1573, 2025.

[32] T. Alharbi, A. Abdalrahman, M. H. Mostafa, and L. Alkhalifa, "Joint optimization of EV charging and renewable distributed energy with storage systems under uncertainty," *IEEE Access*, vol. 13, pp. 76838–76856, 2025.

[33] M. H. Alsharif, F. Alsaif, M. K. Singla, S. Manna, and M.-K. Kim, "Techno-economic optimization and environmental analysis of a solar-powered Electric Vehicles (EVs) charger system for a greener transportation ecosystem," *Energy Reports*, vol. 13, pp. 5803–5814, 2025.

[34] D. Wang, X. Chen, X. Liu, Y. Li, Z. Piao, and H. Li, "Dynamic tariff adjustment for electric vehicle charging in renewable-rich smart grids: A multi-factor optimization approach to load balancing and cost efficiency," *Energies*, vol. 18, no. 16, p. 4283, 2025.

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