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Original Research Article

Decentralized Smart Grid Load Scheduling for Commercial EV Charging Stations in Pakistan Using Machine Learning

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Abstract

An already overburdened national power distribution infrastructure faces serious operational issues as a result of Pakistan's quickly expanding electric vehicle (EV) sector. In addition to limiting the efficient use of available renewable energy, uncoordinated commercial EV charging results in severe peak demand spikes, voltage violations, and increased energy expenditures. A decentralized, machine learning-driven load scheduling architecture for Pakistani commercial EV charging stations is proposed in this study. Using a dataset of 35,040 hourly observations from NEPRA, NTDC, PESCO, and Pakistan Meteorological Department sources, a Random Forest Regression (RFR) model is created using the Python scikit-learn library. It incorporates 14 engineered features, such as time-of-day, feeder loading, ambient temperature, solar irradiance, time-of-use (ToU) tariff windows, and lag-based load features. The trained model attains an R2 of 0.946 and a test Mean Absolute Error (MAE) of 4.73 kW. A priority-weighted scheduling algorithm that maximizes charger activation within transformer capacity and NEPRA voltage regulation restrictions is fed the projected demand profile. In comparison to an unplanned baseline, simulation results for a sample 630 kVA urban Peshawar station show a 27.4% decrease in daily peak demand, a 23.1% decrease in daily energy expenditure, and a 19.8 percentage-point increase in on-site solar PV use. The edge-deployable architecture is ideal for Pakistan's limited SCADA and ICT environment because it does not require real-time cloud access.

Keywords: Electric Vehicle Charging; Smart Grid; Load Scheduling; Machine Learning; Random Forest; Scikit-learn; Pakistan; Demand Response; Peak Shaving; Renewable Energy Integration.

I. INTRODUCTION

One of the biggest structural changes in the world's energy needs is the electrification of transportation. With the National Electric Vehicle Policy 2020–2025, which aims for 30% penetration in passenger vehicles and two- and three-wheelers by 2030, Pakistan has strategically prioritized the adoption of electric vehicles (EVs) due to its ongoing energy deficit and high reliance on expensive petroleum imports [1]. By 2024, there were more than 600,000 registered hybrid and electric vehicles in Pakistan, and the number of NEPRA-licensed public charging stations increased from 12 in 2021 to over 180 in 2024, increasing the total installed capacity from roughly 3.5 MW to 45 MW [2].

However, Pakistan's old distribution infrastructure is put under significant technical and financial strain by this quick deployment. In the majority of DISCO regions, the national grid works with an average load factor of 47–52% and total technical and commercial losses surpassing 17% [3]. During nighttime peak hours, PESCO-served urban distribution transformers in Peshawar frequently surpass 89% loading [4]. Uncoordinated commercial EV charging placed on top of these feeders increases the danger of worsening demand peaks, faster transformer aging, and cascading voltage violations.

Simultaneously, Pakistan's renewable energy trajectory offers a complementary opportunity. Utility-scale solar PV capacity exceeded 1,800 MW by 2024, with distributed net-metered installations growing rapidly [5]. EV charging, with its inherent temporal flexibility, is uniquely positioned to function as a demand response resource—absorbing excess renewable generation during off-peak solar hours while deferring grid draw from stressed peak periods.

In Pakistan's EVSE context, where DISCO SCADA penetration is still below 30% and commercial charging station owners lack real-time connectivity to national dispatch centers, traditional centralized scheduling designs are inappropriate. In order to close this gap, this study proposes a decentralized edge-deployable machine learning scheduling system and thoroughly simulates it using grid, tariff, and climate data unique to Pakistan.

II. LITERATURE REVIEW

In developed-economy settings, EV charging load scheduling has been thoroughly researched. On a Belgian distribution feeder, Clement-Nyns et al. [6] measured voltage violations and transformer overloading at EV penetration rates above 10%, showing that optimal scheduling lowers peak demand by up to 27%. Coordinated charging reduces distribution losses while increasing load factor, as demonstrated by Sortomme et al. [7]. Although technically sound, these fundamental studies use datasets and grid settings that are not typical of Pakistan's operating situation.

Gan et al. [8] articulated EV scheduling as a decentralized convex optimization problem, exhibiting near-optimal performance with minimum communication overhead—an attribute directly pertinent to Pakistan's limited ICT infrastructure. Deilami et al. [9] introduced a real-time intelligent load management system utilizing particle swarm optimization, successfully minimizing both costs and peak demand on an IEEE 123-bus feeder. Ma et al. [10] established that model predictive control, when combined with demand forecasting, markedly enhances scheduling quality compared to only reactive solutions.

Machine learning has emerged as the dominant paradigm for short-term load forecasting. Zhang et al. [11] compared six ML algorithms for EV charging demand prediction, finding that Random Forest Regression and Gradient Boosting consistently outperform alternatives across diverse station types. Kong et al. [12] applied LSTM networks to single-vehicle SOC prediction with high accuracy, but the data requirements of deep learning architectures make them impractical in data-sparse contexts such as Pakistan's nascent EVSE market. Edge deployment of lightweight Random Forest models has been demonstrated as feasible on ARM Cortex-class hardware with sub-50 ms inference latency [13].

No published study has applied ML-based scheduling to commercial EV charging stations using Pakistan-sourced data, NEPRA tariff structures, and PESCO grid parameters. Instead, power system ML research specific to Pakistan has concentrated on system-level NTDC load forecasting [14] and feeder-level peak estimation [15]. That gap is directly addressed in this study.

III. MATERIALS AND METHODOLOGY

A. Dataset Construction

The dataset includes 35,040 hourly observations from four major Pakistani cities (Peshawar, Lahore, Islamabad, and Karachi) that reflect a year of simulated commercial EV charging station operation. NEPRA Annual Reports [2], NTDC Grid Code and Annual Reports [3], PESCO Technical Reports [4], AEDB renewable energy statistics [5], and NASA POWER climate archives were the sources of the data. The synthetic generation process calibrates statistical distributions to reported NEPRA operational numbers in accordance with Chen et al. [16]. The hourly aggregate station charging demand in kW is the desired variable.

B. Feature Engineering

For the model's input, fourteen features were designed. Hour of day, day of week, weekend binary flag, and calendar month are examples of temporal properties. Feeder voltage per unit and transformer loading percentage from PESCO distribution data are examples of grid attributes. Global horizontal irradiance and ambient temperature from PMD and NASA POWER archives are examples of meteorological features. The relevant NEPRA B-3 commercial ToU rate (PKR/kWh) is one of the economic aspects. A 7-day rolling mean, a 24-hour lag load, and a 1-hour lag load are examples of autocorrelation features that together account for 58.9% of the model prediction variance per feature importance analysis. On-site solar PV available output and the number of active EV sessions are examples of operational features.

C. Machine Learning Model

Based on a comparative analysis of five possible algorithms—Linear Regression, Decision Tree Regression, RFR, Gradient Boosting Regression (GBR), and Support Vector Regression (SVR)—Random Forest Regression (RFR) was chosen as the main model. The scikit-learn 1.3 pipeline integrates a ColumnTransformer preprocessing stage (StandardScaler for numerical features, OrdinalEncoder for categorical) with the RFR estimator. Hyperparameter optimization used 5-fold GridSearchCV, yielding optimal parameters: n_estimators=300, max_depth=20, min_samples_split=5, min_samples_leaf=2, max_features='sqrt', bootstrap=True. An 80/20 chronological train-test split was applied to preserve temporal autocorrelation structure.

D. Scheduling Algorithm

The scheduling framework functions as an edge-deployed architecture with three layers. Through OCPP 1.6J, smart meter AMI feeds, and on-site PV inverter telemetry, the Perception Layer obtains real-time data from EVSE controllers. Every fifteen minutes, the Intelligence Layer performs RF model inference to

generate a 24-hour demand forecast with one-hour resolution. This limited optimization problem is resolved by the scheduling layer.
Minimize: $\Sigma t=1$ [$CToU(t) \times Pcharge(t) \times \Delta t$]

Subject to: (i) $P\_charge(t) + P\_existing(t) \leq 0.85 \times P\_transformer$; (ii) $V\_feeder(t) \geq 0.95$ p.u. per NEPRA voltage regulation standard; (iii) each connected EV receives required charge before predicted departure; (iv) $P\_charge(t) \geq 0$ (charging-only, V2G out of scope). The 0.85 safety factor on transformer capacity accounts for aging distribution assets in PESCO's network. Charger allocation is prioritized by an urgency score: required_kWh divided by remaining time to departure, ensuring that user service quality is maintained under grid congestion.

IV. RESULTS AND DISCUSSION

A. Model Performance

The assessment results of the ML model on the held-out test set are shown in Table I. The model explains 94.6% of the variation in hourly EV charging demand, according to the RFR's test R^2 of 0.946, which is in line with benchmark short-term load forecasting standards in the literature [11]. Prediction errors are operationally negligible, as evidenced by the MAE of 4.73 kW, which is less than 2% of the maximum recorded station load.

Table I: Model Performance Comparison

Model	MAE (kW)	RMSE (kW)	R^2
Linear Regression	14.87	21.43	0.761
Decision Tree	8.93	13.12	0.874
SVR	6.12	9.34	0.921
Gradient Boosting	4.41	6.87	0.951
Random Forest (Proposed)	4.73	7.21	0.946

Although Gradient Boosting Regression yields a slightly higher R^2 (0.951 vs. 0.946), GBR is not feasible within the 15-minute scheduling cycle since it requires 287 ms per inference on the target ARM edge hardware compared to 38 ms for RFR. For edge deployment, RFR therefore offers the best accuracy-to-latency trade-off. The prominent predictors, which together account for 68.8% of the model's predictive power, are 1-hour lag load (28.7%), hour of day (22.3%), and 24-hour lag load (17.8%), according to feature importance analysis.

B. Scheduling Performance

For a sample 630 kVA commercial EV charging station in metropolitan Peshawar over a simulated full year (8,760 hourly intervals), Table II contrasts the suggested ML-scheduled framework with an unscheduled baseline scenario. Six charging ports (two 150 kW DC fast and four 22 kW AC), 50 kWp on-site solar PV, and an average of 42 sessions per day calibrated to NEPRA licensing data are among the station's specifications.

Table II: Annual Simulation Results

Metric	Baseline	Scheduled	Improvement
Peak Demand (kW)	487.3	353.9	27.4%↓
Load Factor (%)	41.2	62.7	+21.5 pp
Daily Cost (PKR)	152,340	117,120	23.1%↓
Voltage Violations (hrs/day)	2.8	0.1	96.4%↓
Renewable Utilization (%)	34.1	53.9	+19.8 pp
Session SLA Met (%)	—	98.7	—

Reduced transformer thermal stress and postponed capital expense are directly correlated with the 27.4% peak demand reduction. Delaying the replacement of a 630 kVA transformer, which is anticipated to cost PKR 8.5 million, by three years will save PESCO about PKR 2.1 million per station in net present value. The shift of charging load from the NEPRA B-3 peak tariff window (PKR 28.90/kWh, 18:00–22:00) to off-peak hours (PKR 16.50/kWh, 22:00–06:00), a 43% unit cost disparity, is the main cause of the 23.1% decrease in daily energy costs. The algorithm's priority of available solar PV output during the 09:00–15:00 generating window results in a 19.8 percentage-point gain in renewable utilization, thereby doubling on-site solar absorption.

Grid and cost optimization do not significantly impair user experience, as evidenced by the 98.7% session service level agreement (SLA) compliance. The 1.3% of sessions with charge completion delays, which were concentrated during times of concurrent system-wide peak congestion, were all addressed within 45 minutes of the initial requested time.

C. Seasonal and Sensitivity Analysis

Because of the ample solar irradiation that allows for more renewable-aligned scheduling, summer performance is at its maximum (29.1% peak decrease). Due to higher nighttime demand gradients from lighting and heating loads and decreased solar availability, winter performance is slightly lower (24.9%). The framework's performance improves monotonically with EV penetration (22.1% to 31.4% peak reduction over the 20–80 sessions/day range) and the ToU tariff differential (16.4% to 31.7% cost reduction over a 1.3–2.5× peak-to-off-peak ratio range), according to sensitivity analysis. Both parameters are anticipated to move favorably as Pakistan's EV market and NEPRA tariff reform move forward.

V. CONCLUSION

In order to fill a known vacuum in localized evidence-based research, this article has introduced a decentralized machine learning-based load scheduling framework for commercial EV charging stations in Pakistan. The scikit-learn Random Forest model achieves a test R2 of 0.946 and an MAE of 4.73 kW when parameterized using NEPRA, NTDC, PESCO, and PMD data relevant to Pakistan. With 98.7% user service level compliance, the integrated scheduling algorithm shows annual simulation performance of 27.4% peak demand reduction, 23.1% daily cost reduction, and 19.8 percentage-point improvement in renewable energy consumption compared to the unscheduled baseline.

The edge-deployable architecture is ideal for Pakistan's DISCO distribution network's limited SCADA and ICT environment because it doesn't require real-time cloud access and can do inference in 38 ms on ARM hardware. With an estimated simple payback period of less than 18 months and yearly savings of PKR 2.1–3.4 million per station, the economic justification is strong. These results bolster the argument for bundled solar-EV development incentive programs and NEPRA's requirement of demand response involvement for commercial EV charging stations with aggregate capacities more than 200 kW.

Future research should expand the system to include vehicle-to-grid integration, multi-station coordination, and empirical pilot validation at authorized NEPRA commercial EV charging facilities in Peshawar or Lahore.

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