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Sustainable e-mobility with controlled charging scheme based on grid energy using machine learning

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ABSTRACT

The electric vehicle (EV) popularity has taken off among consumers, which has in turn led to efforts to create an efficient EV charging infrastructure. This paper addresses this challenge by proposing a scheduled charging scheme that uses real-time data from a grid-connected charging station at Baner, Pune, operated by Pune Mahanagar Parivahan Mahamandal Ltd (PMPML). The proposed system makes use of advanced machine learning techniques such as the Stochastic dual coordinate ascent (SDCA) and Fast Forest (FF) algorithm, both of which allow for precise and efficient computations to predict charging finish times and make optimal scheduling decisions. The use of these algorithms in conjunction with ToU tariffs is cost effective when compared to flat rate tariffs. Grid load analysis shows that scheduling according to time lowers peak demand, equalizes load distribution, and lowers operating costs. A quantitative comparison has demonstrated both grid stability and economic efficiency gains over uncontrolled charging. The result is an extremely flexible framework for different charging events or stations which will be a viable way of managing energy in the fast-growing EV charging networks.

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1. INTRODUCTION

Electric vehicles (EVs) are promising both in terms of environmental and economic benefits, as well as increasing availability and acceptance. So, the government of India has launched several initiatives and policies that aim to encourage the widespread use of EVs and inspire a greener, sustainable future. Such initiatives will focus on spreading knowledge to the public and creating incentives through infographics and financial assistance for those seeking EVs.

We need to improve forecasts for charging times of electric vehicles which reflect factors such as the cost savings, enabling us to make a more efficient transition from green energy to clean energy in terms of both air quality and carbon dioxide emissions. As the demand for EVs increases and demand response becomes more critical, charging timetables for EVs need to improve in order to maintain grid stability and ensure our sustainable future: i) we need to keep our charging times as short as possible; ii) improve the timing of charging; iii) track the state of charge (SOC); and iv) optimize charging schedules. Predicting the demand for electricity [1], which has been investigated in numerous studies on financial goals. In this paper, we proposed an electric vehicle scheduling using time sensitive pricing. The proposed multi-agent deep neural network in [1] was trained for important battery energy management aspects such as travel time, range uncertainty, expected departure time, and battery storage capacity.

In general, energy efficiency, energy management, and cost reduction strategies are employed [2]. Shows that the data on the timing of charging, reliability of power grid, and affordability of electric vehicle charging are variable across locations. A real-time scheduling method [3] is employed to make dynamic adjustments to the initial day-ahead plan to ensure that the scheduling is precise and grid stability is maintained. Integrating EVs into the power grid brings some complexities and uncertainties that can pose challenges for traditional stability and reliability assessments. The statistical predictions are often incorrect, which can significantly impact the dependability of the day-ahead planning of charging power allotted to each EV.

Electric vehicle charging has been proven to be more reliable and efficient in real-world scenarios when factors such as charging station locations, travel distances, and external conditions, including traffic and weather, are taken into account [4]. A deep reinforcement learning (DRL) methodology was employed to optimize decision-making under these complex conditions. These conditions are also characterized by uncertainty, making DRL suitable for handling such scenarios [5].

In the previous study [6], the implementation was carried out in two successive stages. Initially, an optimal day-ahead power scheduling plan at the grid connection point (GCP) was developed, followed by the deployment of a real-time model predictive control (MPC) approach. This strategy utilizes the flexibility of electric vehicle charging stations (EVCS) to precisely track the dispatch schedule and ensure reliable and responsive grid performance.

Cao *et al.* [7] redefined the online optimization problem and introduced two actor-critic learning algorithms stochastic continuous actor (SCA) and critic-assisted learning with continuous actions (CALC). These algorithms were designed to enable continuous charging actions and improve adaptive, real-time decision-making to address the challenges presented by dynamic and uncertain EV charging environments. This work estimated that EV charging cost of CALC was 5.56% higher than that of SCA but 7.24% lower than that of adaptive energy management (AEM). CALC demonstrated significantly higher computational efficiency and achieved near-optimal performance compared to SCA.

2. RELATED WORK

Recent work has shown the ability to apply deep learning (DL) to complex systems. Gupta *et al.* [6] achieved a 99.97% accuracy in internet of things (IoT) intrusion detection systems (IDS) using a hybrid LSTM-swin transformer and transfer learning. This performance is comparable to that achieved with traditional DL models.

In power systems, researchers are integrating components such as EV to improve the grid. Previous studies [8] and [9] incorporated electric vehicles into demand response strategies for the day-ahead planning in order to obtain net profit and surplus power at the expense of grid limitations and actual data, such as State of Charge (SOC). This move toward optimization reflects the growing use of predictive analytics; lines [9] examined linear regression for energy consumption, and another study [10] examined machine learning tools to plan for charging and forecast cost-effective strategies. Pan *et al.* [10] described the non-convex nature of this issue and proposed an improved hybrid algorithm that combines particle swarm optimization (PSO) and the gravitational search algorithm (GSA) to make better the allocation of EV charging and discharging power. Pan *et al.* [10] examined machine learning tools that can predict optimal solutions for cost-effective models. Charging scheduling solutions are made more effective through the use of machine learning algorithms. Phan *et al.* [9] investigated the application of linear regression analysis for forecasting energy consumption in real-world scenarios, aiming to enhance predictive accuracy and support data-driven decision-making in energy management systems.

Research on energy systems often employs machine learning for predictive and optimization tasks. Specifically, the utility of general machine learning tools for forecasting energy consumption [9] and enhancing the effectiveness of cost-effective charge scheduling solutions [10] has been established. While papers [11], [12] establish the need for and efficacy of algorithmically superior optimization techniques in the general ML domain.

In order to maximize smart EV charging, another research study considered a dynamic tariff framework. The suggested approach, which used a machine learning model, was described. This research examined the combined challenges of pricing and scheduling for electric vehicle charging from the viewpoint of a charging station operator [13], [14]. The objective is to develop pricing algorithms that encourage the participation of electric vehicle users in the charging network. These algorithms aimed to optimize charging times per charger, ensuring full energy delivery within each user's available time window.

Deep learning (DL) models provide considerable improvements in performance for intricate tasks. Nonetheless, their unclear black-box characteristics require investigation into methods that promote interpretability. Consequently, the integration of Explainable AI (XAI), as highlighted in recent studies [15], [16] is vital for the important shift towards transparent and reliable decision-making which is necessary for the effective implementation of clinical or critical systems.

Researchers in [2], [17] proposed a method that included the time of use (TOU) price-based demand response model and dynamic grid to vehicle (G2V) charge scheduling for electric vehicle aggregator (EVA) that optimizes regulation services and charging costs simultaneously. Previous study [18] proposed a peak-shaving optimization model to minimize power grid losses through prioritized and coordinated charging and discharging activities. Devi *et al.* [19] focus the linear regression demand forecast (LRDF) that can be used to generate more accurate demand forecasts using machine learning approaches along with enough historical data on demand forecasts, product forecasts, and sales projections.

Shalev-Shwartz and Zhang [11] provided a thorough analysis of the stochastic dual coordinate ascent (SDCA) algorithm. Their study demonstrated that its optimization strategies provided strong theoretical guarantees. These guarantees were at par with or better than those of conventional optimization techniques. Conscious of the importance of algorithmic efficiency for practical use, Yates and Islam [20] developed the FastForest algorithm. The algorithm was evaluated to assess its performance. It significantly increased the speed of random forest processing without compromising prediction accuracy.

In terms of technology, Fares *et al.* [16] proposed a multi-purpose plan for EV charging infrastructure that balances environmental goals and grid demand. The proposed strategy is an optimization plan focused on three goals. These goals are boosting EV capacity, cutting carbon dioxide emissions, and lowering both investment and operating costs of the devices.

This paper focuses on addressing this gap by utilizing an efficient machine learning architecture. The proposed architecture can implicitly learn and generalize the constraints needed for optimal and grid-aware charge scheduling. The current work aims to connect advanced optimization principles with a charge scheduling framework.

3. CHALLENGES AND SOLUTIONS

The following are the challenges to achieve smooth EV charging demand and response. Figure 1 highlights the relationship between demand response in the electrical grid and optimal EV charging, and the key benefits of optimal EV charging are included. It also shows the solutions to the challenge for grid parameter maintenance [21], [22]. EV consumers face many challenges shown in Table 1, which also explains machine learning as well as other solutions for consumers.

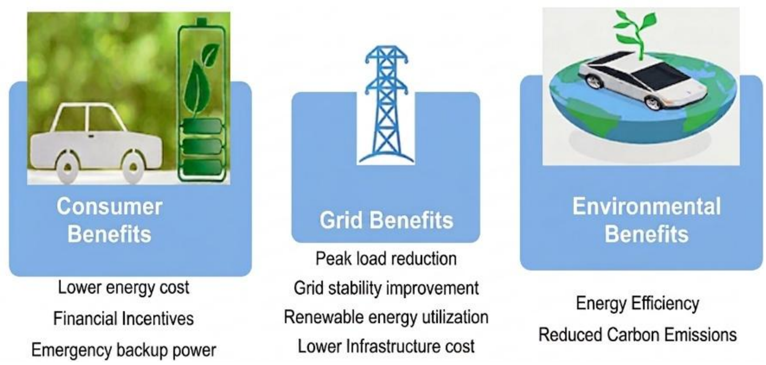

Figure 1. Demand response of EV

Table 1. Challenges for smooth demand response

Challenge	Solution
Security risks	Blockchain and encrypted communication protocols
Individual agreement	Enticements and cost savings for off-peak charging
Grid fluctuations	Real-time monitoring and smart charging alterations
Peak load demand	AI-based dynamic pricing and demand response

4. SMART EV CHARGING SCHEDULING

The scheduling of smart charging effectively integrates automation for electric vehicles with sophisticated communication methods and intelligent management systems. This collaboration enhances the efficiency and effectiveness of charging electric vehicles. The primary goal is to lower expenses and enhance energy efficiency within the grid [22].

5. SYSTEM ARCHITECTURE

In this study, the focus was on an artificial intelligence driven energy management system, which's really important to the overall system plan. The artificial intelligence driven energy management system is a part of this project [23]. The AI-driven energy management system AIDMS system, shown in Figure 2, uses math to forecast energy loads and adjust how much power is used to charge from the grid. It aims to optimize energy use. Ordered data was detected. The data helped transfer and identify loads. The dynamic pricing model managed transmission, distribution, and utilization. This happened at charging points. These points were available at the corresponding charging station. Ultimately, the AIDMS, the linear regression algorithm for energy management could be a cheaper option, similar to the grid. There were some problems though.

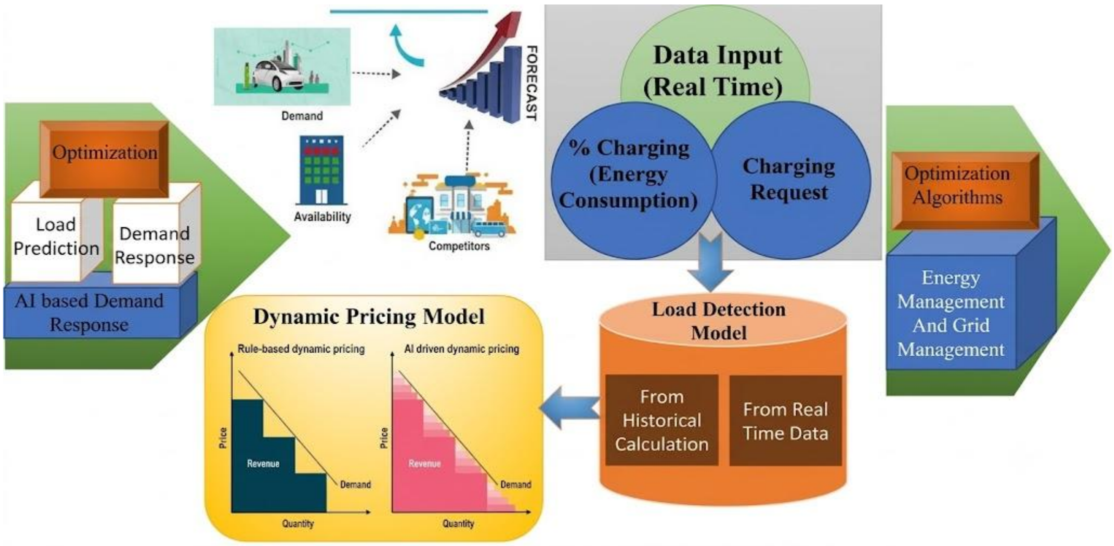

Figure 2. AI-based energy system architecture of EV

6. ELECTRIC VEHICLE CHARGING TARIFF

The pricing models for electric vehicle charging is electric vehicle charging prices are also affected by how power everyone else is using at the same time. These things that decide the cost include how power the electric vehicle uses, how fast it charges and how long it is plugged in [21]. As electric vehicles have become more popular in the past decade, utilities have had to rethink their approach to managing energy demand. By controlling energy-consuming devices and devices that consume more energy, utilities can manage energy demand more effectively [21], [22].

7. MACHINE LEARNING TOOLS

Machine learning tools utilize various techniques for building and deploying models that learn from data. Various machine learning models were used, such as Linear regression, stochastic dual coordinate ascent (SDCA) and Fast Forest (FF) machine learning model to optimize the energy distribution and charging schedules of EVs.

7.1. Linear regression

The value of a variable is predicted using linear regression analysis by reference to its value. The dependent variable is the one you wish to predict. In regression analysis, the independent variable(s) are the predictors used to model and forecast the value of the dependent variable. The analysis works by estimating the equation's coefficients, which quantify the relationship between the independent variable(s) and the best predicted value of the dependent variable [11]. Linear regression fits a straight line to the discrepancies between expected and actual output values or to realize the best-fit line for a set of corresponding numbers.

7.2. Linear regression for energy grid

Linear regression fits a straight line to the discrepancies between expected and actual output values or to realize the best-fit line for a set of corresponding numbers [10]. The value of C (dependent variable) from P (independent variable) is estimated by (1).

$$P = MC + D \tag{1}$$

As per the correspondence, the line equation M is represented by (2).

$$M = \frac{\Sigma(C-\bar{C})(P-\bar{P})}{\Sigma(C-\bar{C})2} \tag{2}$$

In this way, the value of M in the linear regression method is calculated to find the best fit line. In (2), charging price is represented as C, $\bar{C}$is mean of C. On a similar note, P represents charging power, $\bar{P}$ is the mean of P. To avoid nullification of error difference between the actual and predicted values, the sum of square actual charging price minus mean charging price is used. Then D is to be estimated by putting mean values of P and C in (3).

$$\bar{P} = M\,\bar{C} + D \tag{3}$$

In linear regression, R2 represents how the line predicts the actual points to have a better energy model to minimize residual error. R2 is calculated as (4) and (5).

$$R2 \;=\; 1 - \frac{sum\ squared\ regression\ (SSR)}{total\ sum\ of\ squares\ (SST)} \tag{4}$$

$$R2 \;=\; 1 - \frac{\sum_i (Pi-\hat{P}i)^2}{\sum_i (Pi-\bar{P}i)^2} \tag{5}$$

Where Pi is the actual value and P hat is the predicted value.

This statistical model is cast-off to predict forthcoming consequences with minimum mean square error [10]. So linear regression is an admirable possibility for estimating energy performance in electric vehicle charging stations and electricity grids under (6).

$$Min \sum_{t=0}^{T} CtPt\ \Delta t \tag{6}$$

Where Ct is the electricity price at time; Pt is the charging power at time; Δt is the time interval; and T is the total time horizon. Subject to constraints as (7) and (8).

$$Pmin \le Pt \ge Pmin \tag{7}$$

$$\sum_{t=0}^{T} Pt\ \Delta t = Ereq \tag{8}$$

Where $Ereq$ is the required charging energy for an EV.

The error metrics mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE) quantify the magnitude of prediction errors and are defined in the original units of the target variable total charging time in minutes. Error metrics have been evaluated using (9) to (11), respectively.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Pi \ - \hat{P}i| \tag{9}$$

Where $|\mathrm{Pi}\ - \hat{\mathrm{P}}\mathrm{i}|$ is the absolute error for a single observation.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} |Pi \ - \hat{P}i|^2 \tag{10}$$

Where $|\mathrm{Pi}\ - \hat{\mathrm{P}}\mathrm{i}|^2$is the squared error for a single observation.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} |Pi \ - \hat{P}i|^2} \tag{11}$$

This model, particularly in large-scale grid operations, can also be rummage-sale price optimization and grid load balancing.

7.3. Stochastic dual coordinate ascent

SDCA is generally used for optimizing penalized linear models, such as support vector machines, logistic regression frameworks, and conventional linear regression frameworks. SDCA differs from traditional gradient optimization methods by performing updates in the dual space and altering only one coordinate, meaning the dual variable for an individual training data point during each step. The optimization algorithms such as stochastic gradient descent (SGD) [11] directly optimize the primal loss function while SDCA optimizes the dual problem. SDCA works with dual variables and dual objective function to solve the problem.

To solve the original primal optimization problem focused on finding the optimal model weights, SDCA reformulates it into an equivalent dual problem, which it then addresses. SDCA performs iterative updates to the dual variables with new variables from transforming the problem to the dual domain. The approach modifies each dual variable individually rather than updating all at once, which is referred to as coordinate ascent. 'Stochastic' means that the algorithm adjusts the dual variables based on a randomly selected training example at each iteration. The goal of SDCA is to optimize the dual objective function, which is closely linked to the primal loss function, and due to their strong duality, maximizing the dual objective effectively minimizes the primal loss [24], [25].

7.4. Fast Forest (FF)

As part of the ensemble learning process, FF constructs multiple decision trees and generates predictions either by averaging the outcomes for regression tasks or by employing majority voting for classification tasks. This approach aims to harness the strengths of various decision trees, enhancing both accuracy and resilience while steering clear of over-fitting [25], [26]. With Fast Forest, you can predict how much energy an electric car will use, analyze user behavior, and predict energy load needs for your building.

8. METHOD

The power grid's condition is constantly changing, with each moment showing a different state of the trend. Current methods focus only on the current state of the power system, which helps explain how the grid is operating. The optimization model enhances energy distribution efficiency and identifies optimal charging times for electric vehicles. In a flowchart represented in Figure 3, it is shown that training a linear regression model involves identifying the optimal line that reduces the discrepancy between predicted and actual values, in order to facilitate future predictions.

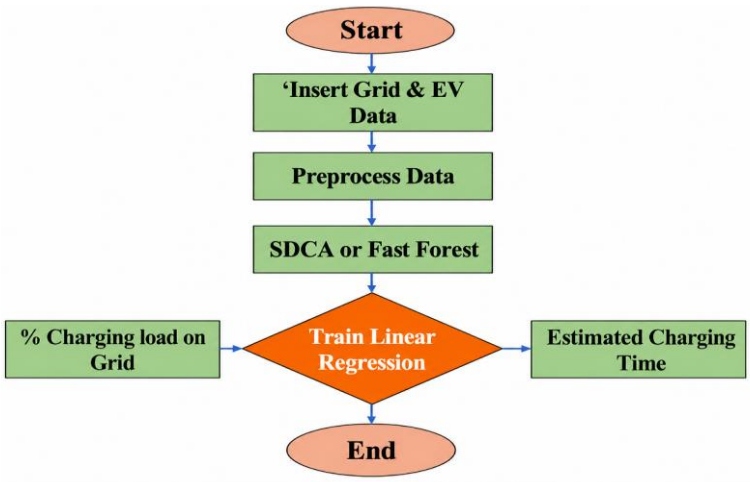

Figure 3. Flowchart for integrated optimization and regression model

Data from grids and electric vehicles are collected, including metrics such as system load, voltage, charging performance, and energy storage capacity. Data preparation is followed by preliminary modeling methods such as FF and SDCA that improve prediction accuracy. EVs are given an estimate of the charging time and a percentage of the grid's charge load. These results are important in understanding the impact of EVs to the grid over time, particularly in terms of load management and peak demand. The model provides real-time and predictive insights into charging and grid stress, as well as making planning, infrastructure, and policy decisions to make the power grid more efficient and resilient. We chose linear regression, stochastic dual coordinate ascent, and FF models because they offer a good base to test our idea. linear regression is simple to understand and will help us see how much better the performance gets when we switch to more complex models.

SDCA was chosen due to its exemplary performance in optimization and high-capacity training for dealing with the large datasets of modern grid monitoring. An accurate estimation of the maximum performance ceiling achievable by linear classifiers when utilizing advanced, computationally efficient optimization methods. The FF is a high performing ensemble learning model with high accuracy. Based on the accuracy achieved, the model will correctly explain why the performance gain of the proposed model is superior to the most efficient methods.

9. RESULTS ANALYSIS BY SDCA AND FAST FOREST

Using SDCA and Fast Forest, the result was a preference for polarized charging based on three-month conventions of baner PMPML charging stations. The work employed SDCA and FF to better predict charging times of electric vehicles by looking at energy use, grid performance, and past charging patterns. Charges were more efficiently scheduled and peak load impact was decreased.

9.1. Stochastic dual coordinate ascent machine learning model

It addresses this dilemma by focusing on the problem itself. As we show in [12], SDCA has a better linear convergence rate for smooth loss functions than SGD. In addition, SDCA is better than SGD for nonsmooth loss functions such as SVMs. We now consider the long-term effects of SDCA on continuous loss functions despite the challenges of data distribution. SDCA is superior to SGD at training a model of continuous losses [11].

The SDCA model is trained to predict peak charging times for electric buses at Baner charging depot. The quick and efficient processing of large datasets from baner charging stations is used for energy grids enhancement, energy distribution, reduction of costs, and grid performance boosting. SDCA algorithm was exploited to optimize charging time estimation. The graph shown in Figure 4 represents charger vs predicted charging completion time. This evaluation is conducted on Baner (Pune) charging station dataset's a particular.

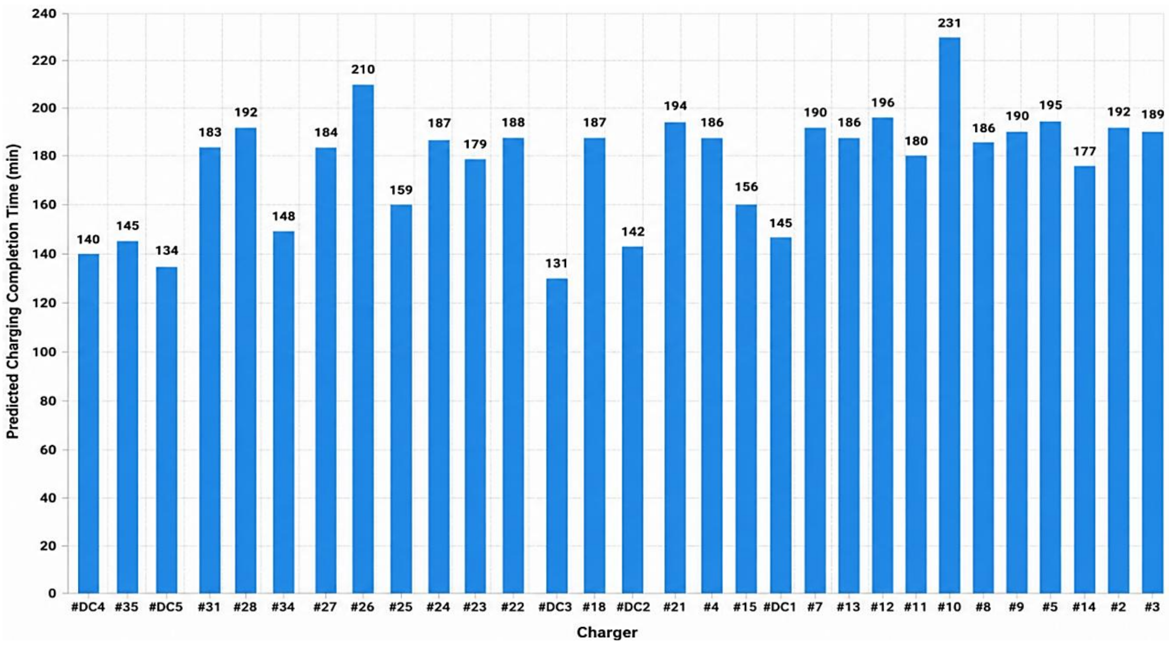

Figure 4. Charging time optimization per charger from SDCA model

Table 2 (see Appendix) represents the performance analysis of the SDCA model, in which the experimented values of R-squared, MSE, MAE, and root mean squared error are presented. The model delivers enhanced predictive accuracy in comparison to linear models. This improvement is observed when the model is applied to real-world data.

9.2. Fast Forest machine learning model

The FF algorithm also tackles the optimization challenge by concentrating on time series forecasting. The FF model, an ensemble regression technique based on gradient-boosted decision trees, is particularly effective in managing non-linear and intricate datasets, rendering it suitable for predicting electric vehicle charging duration [14], [16], [25]. Figure 5 shows the charging time optimization per charger for the FF model over the same charging station dataset.

Table 3 (see Appendix) represents the performance analysis of the FF metric. The calculated values include R-squared, MSE, MAE, and root mean squared error. These metrics were used to evaluate the performance of the FF model.

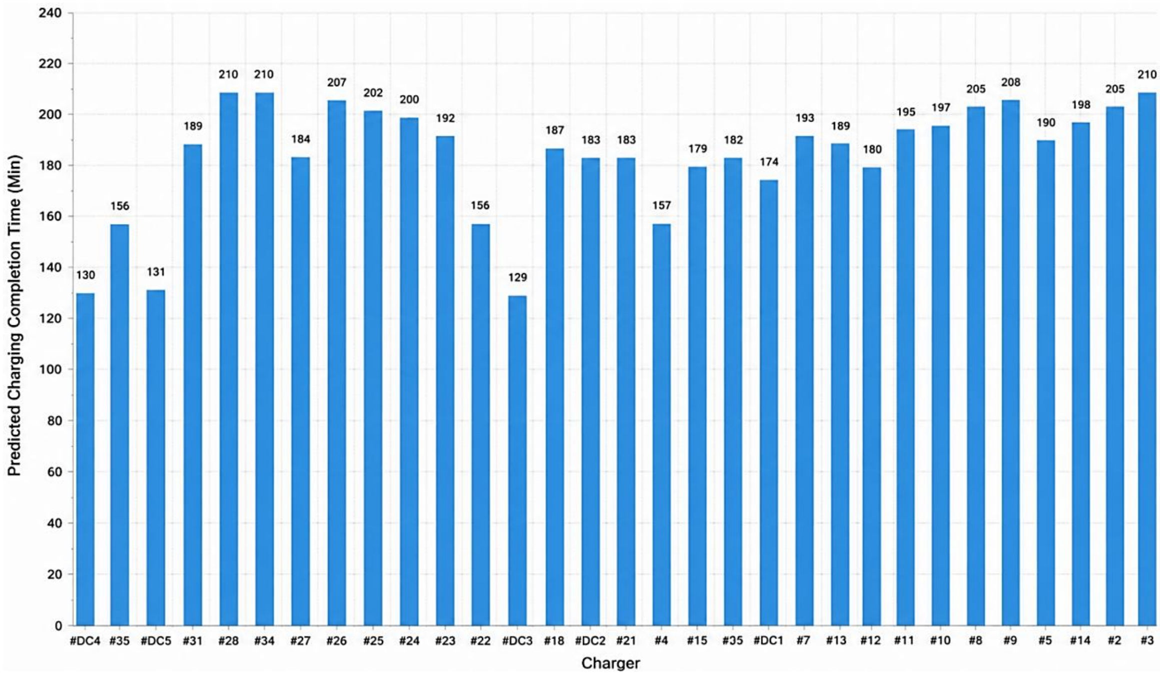

Figure 5. Charging time optimization per charger for FF model

10. COMPARISON OF PRICING MODEL AND CHARGING TIME ESTIMATION

To improve scheduled charging, this work takes into account the comparative cost benefits by analyzing the energy performance of the energy grid. It also implements the SDCA and FF algorithms for an electric bus charging station. These algorithms are used for battery charging time forecasting [26], [27].

Figure 6 illustrates the comparative results of flat rate tariff optimization per charger over time for the SDCA and FF models, demonstrating that the FF algorithm yields superior performance, thereby establishing it as a more cost-effective solution. If model accurately predicts the total energy required ($\hat{P}req$) and when it will be consumed, it can select the most favorable tariff. High accuracy ensures you don't over-commit to expensive tariffs or under-utilize cheap ones. The accuracy of the models' predictions has resulted in a high level of economic benefit, which has been exploited by our optimization engine. Especially impressive was the high R2 values and low error metrics (MAE/RMSE) in Tables 3 and 4, which proved to be crucial in the operation of the PMPML charging station. The high accuracy of the models' predictions about the timing of the charge significantly reduces the tariff as charging sessions are cut from peak Time-of-Use (ToU) periods to cheaper off-peak ones, resulting in the substantial reduction in cost of charging shown in the charging cost comparison graph.

Table 4 compares the error metrics, including R-squared, MSE, MAE, and RMSE, for the two algorithms. A value between 0.6 and 0.8 indicates a good model fit. A value near 1.0 indicates an ideal fit, meaning that the model captures the variability of the response variable around its mean.

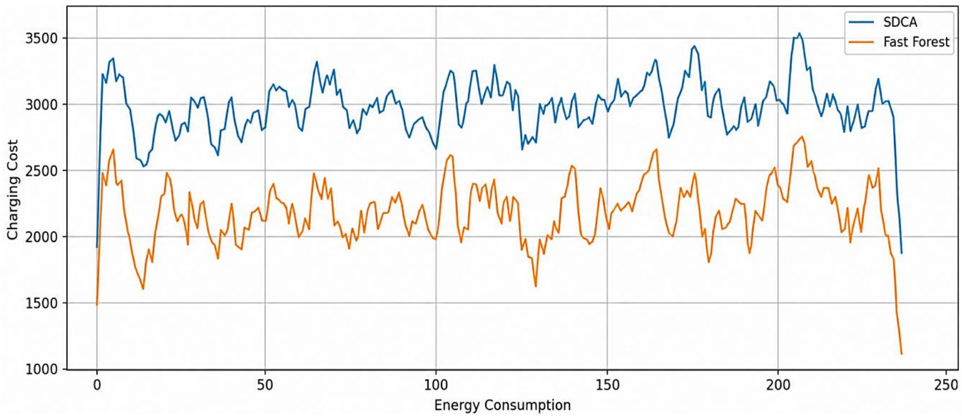

Figure 6. Comparison of tariff for SDCA and FF

Table 4. Comparative evaluation matrix using SDCA and FF

Parameter	SDCA	Fast Forest	SDCA	Fast Forest
Charger name:	DC4	DC4	DC5	DC5
Model evaluation data size	1026	1026	909	909
R-squared	0.6756	0.6778	0.7041	0.6949
Mean squared error	534.18	530.5	554.05	571.19
Mean absolute error	16.21	14.6	14.3	14.83
Root mean squared error	23.11	23.03	23.54	23.9
	SDCA	Fast Forest	SDCA	Fast Forest
Charger name:	23	23	26	26
Model evaluation data size	247	247	258	258
R-squared	0.7552	0.7397	0.5367	0.6508
Mean squared error	536.29	570.2	1222.8	921.52
Mean absolute error	17.87	18.27	26.15	22.23
Root mean squared error	23.16	23.88	34.97	30.36
	SDCA	Fast Forest	SDCA	Fast Forest
Charger name:	22	22	18	18
Model evaluation data size	229	229	211	211
R-squared	0.6484	0.6808	0.7372	0.7229
Mean squared error	762.43	692.17	894.48	943.01
Mean absolute error	16.66	15.67	22.23	23.94
Root mean squared error	27.61	26.31	29.91	30.71
	SDCA	Fast Forest	SDCA	Fast Forest
Charger name:	27	27	25	25
Model evaluation data size	259	259	269	269
R-squared	0.7176	0.7203	0.5978	0.6348
Mean squared error	842.96	834.7	1166.51	1058.96
Mean absolute error	15.73	17.02	22.84	20.78
Root mean squared error	29.03	28.89	34.15	32.54
	SDCA	Fast Forest	SDCA	Fast Forest
Charger name:	21	21	7	7
Model evaluation data size	234	234	137	137
R-squared	0.7926	0.7742	0.7989	0.7941
Mean squared error	658.54	717.1	476.76	488.15
Mean absolute error	17.14	17.28	16.28	17.44
Root mean squared error	25.66	26.78	21.83	22.09
	SDCA	Fast Forest	SDCA	Fast Forest
Charger name:	13	13	12	12
Model evaluation data size	206	206	186	186
R-squared	0.8549	0.8483	0.7739	0.7372
Mean squared error	429.03	448.78	689.38	801.36
Mean absolute error	15.49	15.64	18.59	20.12
Root mean squared error	20.71	21.18	26.26	28.31

11. CONCLUSION

Machine learning’s predictive abilities also helped improve EV charging station energy management. The two main prediction algorithms tested, SDCA and FF, performed well when dealing with real-world data. Both models produced R2 values of over 0.70 on chargers that are highly utilized. This performance indicates that the model can predict more accurately in scenarios with high usage. On all tested chargers, the Fast Forest algorithm performed slightly better in reducing errors. It decreased the median RMSE by about 3% to SDCA, providing a narrower error margin for peak shaving. The high accuracy of these models in forecasting charging durations helped plan accordingly to shift from expensive Time-of-Use (ToU) peak times to cheaper off-peak times, achieving both cost and load equalization. The combination of these scheduling algorithms with linear regression greatly improves energy performance analysis of EV grids. Because regression models are able to prevent unpredictable spikes in load, grid stability can be maintained despite the dynamism created by EV integration.

The current model relies solely on charging station data. It does not factor in any external factors that could affect availability of vehicles such as real-time delays in public transit or micro-weather events at a local level. It also relies exclusively on DC fast charging, but performance may vary to AC Level 2 charging networks with different uses.

Future work will focus on creating a multi-charger aggregation system (MCAS) to better coordinate how electricity use is managed at several PMPML charging stations across different regions. To improve the accuracy of charging demand prediction, external data sources will be integrated. These sources include traffic information and micro-weather data to make the scheduling engine more robust.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Pradeep Mane	✓			✓	✓				✓				✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

No conflict of interest.

DATA AVAILABILITY

The data set utilized for research is sourced from the PMPML Baner Electric Bus Depot in Pune, India. The data collected for this study encompassed a six-month period from May 1, 2023 to October 31, 2023. This data set comprised approximately 3,700 unique charging events collected from DC fast chargers and AC chargers. The input features used for modeling included: charger ID, day of week, time of day, the initial state of charge %SOC, the final %SOC. The target variable for prediction was the charging duration in minutes. The final processed dataset was strategically partitioned for model development and evaluation. The implementation relied on the stochastic dual coordinate ascent (SDCA) algorithm and Fast Forest algorithm separately for optimization. Then comparative effect is analyzed.

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APPENDIX

Table 2. Evaluation matrix using SDCA

Charger no	SDCA	Charger no	SDCA
Charger name	DC4	Charger name	21
Model evaluation data size	1026	Model evaluation data size	234
R-squared	0.6756	R-squared	0.7926
Mean squared error	534.18	Mean squared error	658.54
Mean absolute error	16.21	Mean absolute error	17.14
Root mean squared error	23.11	Root mean squared error	25.66
Charger name	35	Charger name	4
Model evaluation data size	179	Model evaluation data size	150
R-squared	0.5174	R-squared	0.4138
Mean squared error	1401.1	Mean squared error	1255.43
Mean absolute error	29.29	Mean absolute error	22.12
Root mean squared error	37.43	Root mean squared error	35.43
Charger name: DC	DC5	Charger name	15
Model evaluation data size	909	Model evaluation data size	213
R-squared	0.7041	R-squared	0.7033
Mean squared error	554.05	Mean squared error	785.5
Mean absolute error	14.3	Mean absolute error	20.64
Root mean squared error	23.54	Root mean squared error	28.03
Charger name	31	Charger name: DC	DC1
Model evaluation data size	266	Model evaluation data size	309
R-squared	0.7038	R-squared	0.0258
Mean squared error	910.27	Mean squared error	7183.92
Mean absolute error	22.09	Mean absolute error	28.43
Root mean squared error	30.17	Root mean squared error	84.76
Charger name	28	Charger name	7
Model evaluation data size	275	Model evaluation data size	137
R-squared	0.6217	R-squared	0.7989
Mean squared error	1293.25	Mean squared error	476.76
Mean absolute error	18.62	Mean absolute error	16.28
Root mean squared error	35.96	Root mean squared error	21.83
Charger name	34	Charger name	13
Model evaluation data size	229	Model evaluation data size	206
R-squared	0.4983	R-squared	0.8549
Mean squared error	1297.04	Mean squared error	429.03
Mean absolute error	30.56	Mean absolute error	15.49
Root mean squared error	36.01	Root mean squared error	20.71
Charger name	27	Charger name	12
Model evaluation data size	259	Model evaluation data size	186
R-squared	0.7176	R-squared	0.7739
Mean squared error	842.96	Mean squared error	689.38
Mean absolute error	15.73	Mean absolute error	18.59
Root mean squared error	29.03	Root mean squared error	26.26
Charger name	26	Charger name	11
Model evaluation data size	258	Model evaluation data size	190
R-squared	0.5367	R-squared	0.6255
Mean squared error	1222.8	Mean squared error	1137.55
Mean absolute error	26.15	Mean absolute error	23.03
Root mean squared error	34.97	Root mean squared error	33.73
Charger name	25	Charger name	10
Model evaluation data size	269	Model evaluation data size	184
R-squared	0.5978	R-squared	0.0366
Mean squared error	1166.51	Mean squared error	2484.36
Mean absolute error	22.84	Mean absolute error	39.09
Root mean squared error	34.15	Root mean squared error	49.84
Charger name	24	Charger name	8
Model evaluation data size	248	Model evaluation data size	183
R-squared	0.709	R-squared	0.5296
Mean squared error	775.14	Mean squared error	1681.88
Mean absolute error	19.11	Mean absolute error	23.35
Root mean squared error	27.84	Root mean squared error	41.01

Table 2. Evaluation matrix using SDCA (continued)

Charger no	SDCA	Charger no	SDCA
Charger name	23	Charger name	9
Model evaluation data size	247	Model evaluation data size	176
R-squared	0.7552	R-squared	0.883
Mean squared error	536.29	Mean squared error	317.14
Mean absolute error	17.87	Mean absolute error	12.34
Root mean squared error	23.16	Root mean squared error	17.81
Charger name	22	Charger name	5
Model evaluation data size	229	Model evaluation data size	159
R-squared	0.6484	R-squared	0.7891
Mean squared error	762.43	Mean squared error	682.89
Mean absolute error	16.66	Mean absolute error	17.74
Root mean squared error	27.61	Root mean squared error	26.13
Charger name: DC	Dc3	Charger name	14
Model evaluation data size	802	Model evaluation data size	210
R-squared	0.3397	R-squared	0.8308
Mean squared error	1692.44	Mean squared error	349.81
Mean absolute error	16.35	Mean absolute error	13.94
Root mean squared error	41.14	Root mean squared error	18.7
Charger name	18	Charger name	2
Model evaluation data size	211	Model evaluation data size	119
R-squared	0.7372	R-squared	0.1296
Mean squared error	894.48	Mean squared error	812.1
Mean absolute error	22.23	Mean absolute error	21.9
Root mean squared error	29.91	Root mean squared error	28.5
Charger name: DC	Dc2	Charger name	3
Model evaluation data size	798	Model evaluation data size	125
R-squared	0.6396	R-squared	0.6559
Mean squared error	567.07	Mean squared error	470.51
Mean absolute error	15.9	Mean absolute error	15.56
Root mean squared error	23.81	Root mean squared error	21.69

Table 3. Evaluation matrix using FF

Charger no	Fast Forest	Charger no	Fast Forest
Charger name	DC4	Charger name	4
Model evaluation data size	1026	Model evaluation data size	150
R-squared	0.6778	R-squared	0.4548
Mean squared error	530.5	Mean squared error	1167.64
Mean absolute error	14.6	Mean absolute error	23.69
Root mean squared error	23.03	Root mean squared error	34.17
Charger name	35	Charger name	15
Model evaluation data size	179	Model evaluation data size	213
R-squared	0.6905	R-squared	0.7369
Mean squared error	898.54	Mean squared error	696.52
Mean absolute error	21.14	Mean absolute error	21.61
Root mean squared error	29.98	Root mean squared error	26.39
Charger name: DC	DC5	Charger name: DC	DC1
Model evaluation data size	909	Model evaluation data size	309
R-squared	0.6949	R-squared	0.0253
Mean squared error	571.19	Mean squared error	7187.45
Mean absolute error	14.83	Mean absolute error	28.33
Root mean squared error	23.9	Root mean squared error	84.78
Charger name	31	Charger name	7
Model evaluation data size	266	Model evaluation data size	137
R-squared	0.6437	R-squared	0.7941
Mean squared error	1094.75	Mean squared error	488.15
Mean absolute error	23.45	Mean absolute error	17.44
Root mean squared error	33.09	Root mean squared error	22.09
Charger name	28	Charger name	13
Model evaluation data size	275	Model evaluation data size	206
R-squared	0.6969	R-squared	0.8483
Mean squared error	1036.15	Mean squared error	448.78
Mean absolute error	18.46	Mean absolute error	15.64
Root mean squared error	32.19	Root mean squared error	21.18

Table 3. Evaluation matrix using FF (continued)

Charger no	Fast Forest	Charger no	Fast Forest
Charger name	34	Charger name	12
Model evaluation data size	229	Model evaluation data size	186
R-squared	0.7463	R-squared	0.7372
Mean squared error	655.97	Mean squared error	801.36
Mean absolute error	17.23	Mean absolute error	20.12
Root mean squared error	25.61	Root mean squared error	28.31
Charger name	27	Charger name	11
Model evaluation data size	259	Model evaluation data size	190
R-squared	0.7203	R-squared	0.6075
Mean squared error	834.7	Mean squared error	1192.05
Mean absolute error	17.02	Mean absolute error	22.8
Root mean squared error	28.89	Root mean squared error	34.53
Charger name	26	Charger name	10
Model evaluation data size	258	Model evaluation data size	184
R-squared	0.6508	R-squared	0.5681
Mean squared error	921.52	Mean squared error	1113.87
Mean absolute error	22.23	Mean absolute error	21.93
Root mean squared error	30.36	Root mean squared error	33.37
Charger name	25	Charger name	8
Model evaluation data size	269	Model evaluation data size	183
R-squared	0.6348	R-squared	0.5451
Mean squared error	1058.96	Mean squared error	1626.3
Mean absolute error	20.78	Mean absolute error	23.19
Root mean squared error	32.54	Root mean squared error	40.33
Charger name	24	Charger name	9
Model evaluation data size	248	Model evaluation data size	176
R-squared	0.7534	R-squared	0.8218
Mean squared error	656.75	Mean squared error	482.96
Mean absolute error	16.94	Mean absolute error	16.09
Root mean squared error	25.63	Root mean squared error	21.98
Charger name	23	Charger name	5
Model evaluation data size	247	Model evaluation data size	159
R-squared	0.7397	R-squared	0.7445
Mean squared error	570.2	Mean squared error	827.3
Mean absolute error	18.27	Mean absolute error	20.99
Root mean squared error	23.88	Root mean squared error	28.76
Charger name	22	Charger name	14
Model evaluation data size	229	Model evaluation data size	210
R-squared	0.6808	R-squared	0.8794
Mean squared error	692.17	Mean squared error	249.37
Mean absolute error	15.67	Mean absolute error	12.28
Root mean squared error	26.31	Root mean squared error	15.79
Charger name: DC	DC3	Charger name	2
Model evaluation data size	802	Model evaluation data size	119
R-squared	0.329	R-squared	0.2398
Mean squared error	1719.78	Mean squared error	709.23
Mean absolute error	16.8	Mean absolute error	21.3
Root mean squared error	41.47	Root mean squared error	26.63
Charger name	18	Charger name	3
Model evaluation data size	211	Model evaluation data size	125
R-squared	0.7229	R-squared	0.5603
Mean squared error	943.01	Mean squared error	601.18
Mean absolute error	23.94	Mean absolute error	16.46
Root mean squared error	30.71	Root mean squared error	24.52
Charger name: DC	DC2	Charger name	21
Model evaluation data size	798	Model evaluation data size	234
R-squared	0.578	R-squared	0.7742
Mean squared error	663.86	Mean squared error	717.1
Mean absolute error	17.11	Mean absolute error	17.28
Root mean squared error	25.77	Root mean squared error	26.78

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