CA4021 BSc Data Science

Formal Project Proposal

Project Title:	Price Profile Computer Application for EV Charging Stations	
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Executive Summary

Real-time demand for electric vehicle (EV) charging stations is unpredictable although it may be modelled [1] using historical data and machine learning. It lies in the interest of EV charging station owners to fluctuate prices for charging according to forecasted demand [2]. Increasing prices when demand is high will result in more revenue, while decreasing prices when demand is low will entice users to charge, encouraging continuous business turnover [3].

This research aims to develop a dynamic pricing computer application which will generate a price profile document, given historical demand data of an EV charging station. The project will be divided into three stages. In the first stage, we will determine the most accurate demand forecasting model. Machine learning models such as ARIMA, TBATS, LSTM and GRU, will be trained and tested in order to evaluate the most accurate and computationally feasible model. In the second stage we will discuss and choose the most profitable charging pricing algorithm. A simulation will be run on historical data for different pricing algorithms to select the most profitable one. In the third stage we will develop a computer application using Python that generates the recommended price profile for the selected date range.

Section 1: Motivation and Background

As more electric vehicles appear in cities, the demand for charging stations is also increasing [4]. Unlike when charging conventional internal combustion engine vehicles, EV vehicles must be charged at least for 15 minutes due to the battery characteristics [5]. This is most often done either at work or at home [6] which is the most convenient and cheapest option [7], largely due to cheaper electricity tariffs at night [8] but also due to easy access and flexibility of charging time [9]. The frequency of EV charging depends on the journey planned and is rarely daily [10]. Charging demand fluctuates from hour to hour, day to day [11] and season to season [12], which complicates the utilisation and management of charging facilities.

Public charging stations available can be classified into slow-charging or fast-charging stations [13]. Costs that electricity suppliers charge EV charging stations include fixed monthly grid integration charges, peak demand charges, noncoincident demand charges and finally volumetric energy charges, of which peak demand charges are the most significant [14]. One way to reduce these charges is by encouraging charging off-peak hours. Where scheduling control is not feasible, a dynamic pricing algorithm should be implemented providing cheaper charging during off-peak hours and more expensive charging during peak hours [15] [16].

In addition, with the advancement of technology and the development of the market, consumers' expectations for charging services are also increasing. Not only do they want to be able to charge their vehicles quickly [17] and easily, but they also want to be able to access these services at a reasonable price [18]. With this in mind, an accurate demand forecasting model and a competitive pricing model are particularly important. With accurate forecasting of charging station usage, EV charging station owners can better manage and allocate resources [19], while with real-time pricing strategies, they can better balance supply and demand to meet user needs while ensuring economic benefits. Therefore, developing data science methods to accurately predict and reasonably price electric vehicle charging as well as provide easy to use computer applications for owners to implement these methods is both a challenge and an area worth exploring.

Section 2: The Problem Statement

Problem

Users have different needs for charging at different times, dates, locations and situations [20]. Accurate demand forecasting can not only help charging station owners rationally allocate resources, but also improve users' charging experience by spreading demand. With the increase of competition [21] and the change of user needs, a flexible and real-time pricing model is particularly important. Therefore, how to reasonably predict these demands and formulate a real-time pricing model accordingly to ensure the efficient operation of charging stations, maximise on profit and meet the needs of users is a major issue facing the industry at present.

Scope of Work

This study aims to establish the best-performing machine learning model for real-time demand forecasting and the optimal pricing algorithm for EV charging stations. The machine learning model will predict the demand for the charging station based on historical data. Our end goal is to provide a charging station with a pricing strategy for the foreseeable future based on its personal historical data. To accomplish this, we will build a computer application in Python that will accept a charging station’s historical data, train the demand forecasting model and generate a document with the recommended pricing strategy for the selected date range based on the optimal pricing algorithm. In this way, we will provide charging stations with a personal pricing profile that can meet their economic interests using data available to them. We hope to provide valuable insights and solutions to this industry through this study.

Section 3: State of the Art

1. Demand Forecasting

Time series modelling and machine learning modelling are the most popular techniques for EV demand forecasting:

Choi et al. [22] forecasted EV charging demand for Korean regions using ARIMA, ARIMAX, ARIMA-GARCH, ARIMAX-GARCH, SARIMA and SARIMAX. Kim et al. [1] applied different time series and machine learning models to forecast EV charging demand and compared their performance. These models are ARIMA model, artificial neural networks (ANN), long short-term memory (LSTM) and TBATS model. The study considered predictions based on past values, weather, and day effects as an alternative to more inaccessible personal data. Different scopes of geographical analysis were conducted including on a nation, city, and station. Based on this study, we have selected ARIMA, LSTM and TBATS as candidates in our demand forecast analysis. Zheng et al. [23] conducted short-term load forecasting using EMD-LSTM neural networks with a Xgboost algorithm for feature importance evaluation. Zhu et al. [24] compared different deep learning models in short-term load forecasting for EV charging stations. The best performance out of RNN, DNN, GRU and LSTM had GRU. Therefore, we have decided to also include GRU in our analysis.

Ensemble models, hybrid models and probabilistic modelling are also researched:

Gómez-Quiles et al. [25] created an ensemble model composed of ARIMA, GARCH and PSF algorithms and applied it to forecasting EV power consumption in Spain. Dokur et al. [26] presented a new multiple decomposition based hybrid forecasting model for EV fleet charging. The proposed approach incorporated the Swarm Decomposition (SWD) into the Complete Ensemble Empirical Mode Decomposition Adaptive Noise (CEEMDAN) method. Xin et al. [27] applied Edit Distance to the domain of power load prediction to forecast the short-term load of electric vehicle charging stations. Guenoupkati et al. [28] implemented Gaussian Process Regression coupled with a Multilayer Perceptron Kernel to forecast electric load in energy power systems. This method outperformed standard Gaussian process models.

2. Pricing Algorithms

Limmer [29] surveyed the dynamic pricing for EV charging literature and listed static pricing algorithms currently implemented in the United States of America:

These include time-based fees (usually $/min), usage-based fees ($/kWh) session-based charges (fixed price per charging session), TOU (Time-of-use, meaning varying tariff depending on when energy is consumed relative to peak-time) with possible additional charges such as idle charging fee.

Most dynamic pricing research is focused on scheduling control algorithms:

Guo et al. [30] described charging scenarios for EV charging stations: Uncontrolled (greedy), Constrained and Smart charging scenarios. In the first scenario, the charging process immediately starts by using the maximum charging power. In the second scenario, the required energy charged is equally distributed over the entire parking period. In the third scenario, the smart charging process will find the relatively low-price time intervals for charging the EV during its parking period and will make cost-minimising decisions about how and when to charge the EV. Wang et al. [31] discussed how scheduling control of EV charging stations may be achieved using reinforcement learning based real-time pricing. A far-sighted state-action-reward-state-action (SARSA) based algorithm, called HSA, was introduced in the study for pricing decisions for EV charging. Compared with the truncated sample average approximation (SAA) method and the greedy strategy, HSA algorithm provided 20.2% and 132.8% extra profits respectively, showing better economic benefits and higher computational efficiency.

It should be noted that our project does not pursue research on scheduling control pricing algorithms like the aforementioned studies, but on dynamic pricing algorithms assuming constant rate of charge beginning immediately when an EV is plugged in. This could be thought of as dynamic TOU algorithms trained on historical data. Since we have not found any studies proposing similar algorithms, we have decided to develop, propose and evaluate our own algorithms.

3. Machine Learning Models in EV Charging Demand Prediction

I. Long Short-term Memory Network (LSTM)

This article [32] by Sukanya Bag from AnalyticsVidhya provides a comprehensive tutorial on Long Short-Term Memory networks (LSTM) and their implementation. As a special recurrent neural network (RNN), LSTM is able to learn long-term dependencies in time series data, making it excellent at predicting the demand for charging stations. The LSTM makes accurate predictions of EV charging demand patterns by utilising its memory unit to retain past information while forgetting unimportant data, which is particularly useful in dealing with demand fluctuations during peak and off-peak hours.

II. Gated Cycle Unit (GRU)

Sayed Fahim Ali Dawdye from CodingNinjas wrote an article [33] which explores in-depth the method of using Gated Cycle Unit (GRU) for time series prediction. GRU is a variant of LSTM that simplifies the model structure but retains the key features of LSTM. This simplification of the structure can sometimes speed up the training of the model and reduce the risk of overfitting. For real-time EV charging demand forecasting systems, GRUs can provide a more efficient way to process a large number of data points and quickly adapt to changes in demand in real-time applications.

III. Auto Regressive Integrated Moving Average (ARIMA)

ARIMA is one of the traditional methods for predicting time series data. As shown in the tutorial by Selva Prabhakaran available on the Machine Learning Plus website [34], the ARIMA model models and predicts future data points by combining differential (to achieve data stationarity), autoregressive (AR), and moving average (MA) parts. This model is particularly well-suited for processing time-series data with clear trends or seasonality, such as the daily charging patterns of electric vehicles. By customising the model parameters, ARIMA is able to accurately capture cyclical fluctuations in charging demand to provide accurate demand forecasts for charging stations.

IV. Trigonometric, Box-Cox, ARMA errors, Trend & Seasonal components (TBATS)

The TBATS model is a relatively new time series forecasting method that combines several advanced time series components, including the seasonal component of trigonometric transformation and the Box-Cox transformation. As Nadeem [35] demonstrated on Medium, the TBATS model is designed to process time series data with multiple seasonal cycles or non-integer seasonal patterns. Because EV charging demand can be affected by multiple seasonal factors, such as the difference between weekdays and weekends, or different seasons of the year, the TBATS model provides a powerful tool to capture these complex seasonal structures, making forecasting more accurate and flexible.

4. Pricing Ethics

Research into principles of responsible electricity tariffs for utility suppliers would also be relevant in an EV charging dynamic pricing algorithm implementation. Bonbright's *"Principles of Public Utility Rates"* [36] is a work that influenced policy makers including California Public Utilities Commission (CPUC) and its *"Electric Rate Design Principles and Demand Flexibility Design Principles"* [37] adopted in 2023. In his work, Bonbright focuses on the utility's revenue requirement, optimal efficiency in consumption of electricity and *"that rates must be simple, understandable, acceptable, free from controversy in interpretation, stable, and non-discriminatory"* [38]. Noteworthy are CPUC's (vi.) and (vii.) principles which state that: *"Rates should encourage customer behaviours that optimise the use of existing grid infrastructure to reduce long-term electric system costs."* and *"Customers should be able to understand their rates and rate incentives and should have options to manage their bills."*

In summary, planned pricing tariffs for EV charging should encourage a balanced electric load on the network while being fair, visible and logical for users so that they could plan their future use. This is why we ask EV charging station owners using our computer application to make the forecasted demand and pricing profile public to clients one day in advance.

Section 4: Methodology

As our goal is creating a versatile price recommendation computer application, we will be conducting testing on two different datasets. The first is an open data dataset published by the city of Palo Alto in the United States of America [39] and spans dates from July 2011 to December 2020. The second dataset is also an open data dataset published by the town of Cary in the United States of America [40] and spans dates from April 2012 to January 2023.

The features that we chose to include from our datasets:

- Station Name: Identifies the charging station.
- Charging Start Time: The timestamp when the charging session began.
- Charging End Time: The timestamp when the charging session ended.
- Total Duration: The total time the EV was charging.
- Energy Used (kWh): The amount of electrical energy consumed during the charging session.

In the first stage of research, the following algorithms will be tested for forecasting electricity demand: Long Short-Term Memory (LSTM) Networks, Gated Recurrent Units (GRU), Auto-Regressive Integrated Moving Average (ARIMA) and Trigonometric seasonality; Box-Cox transformation; ARMA errors; Trend; Seasonal components (TBATS) model.

To ensure a generic analysis, training and testing will be carried out for every model on every charging station in the two datasets. Each charging station's dataset will be split into training and testing datasets with a 75:25 ratio, which is the same split Admadian et al. [41] used. The models' training and testing will be coded in Python using appropriate libraries. The metrics used to compare the accuracy of demand forecasts will be Normalised Mean Absolute Error and Normalised Root Mean Squared Error [42] which Zhu et al. used for their model evaluation [24].

In the second stage of research, dynamic pricing algorithms will be proposed and evaluated against benchmark algorithms such as time-based fees, usage-based fees and session-based fees. The algorithms will be discussed and a simulation will be run to test their profitability on historical data. In the final stage we will build a Python application that given historical data will create a CSV of the optimal price profile.

Section 5: Project Plan / Gantt chart

	Xi Zhang
	Krzysztof Baran

Semester One Project Plan:

Topic	Activity		Semester 1															
		Date	11/09/23	18/09/23	25/09/23	02/10/23	09/10/23	16/10/23	23/10/23	30/10/23	06/11/23	13/11/23	20/11/23	27/11/23	04/12/23	11/12/23	18/12/23	25/12/23
		Week	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11	Week 12	Week 13	Week 14	Week 15	Week 16
Topic 1: Planning	Project Ideation																	
	Finding Supervisor																	
	Conducting Research																	
	Write Project Proposal Plan																	
	Submit Project Proposal Plan																	
Topic 2: Pre-Processing	Data Wrangling																	
	Data Cleaning																	
	Data Processing																	
Topic 3: Demand Model Building	Implement LSTM model in Python																	
	Implement GRU model in Python																	
	Implement ARIMA model in Python																	
	Implement TBATS model in Python																	
	Run Analysis on Historical Data																	
Topic 4: GitLab	Upload to Gitlab																	
Topic 5: Pricing Algorithms	Describe Pricing Algorithms																	
	Conduct Pricing Simulations for Algorithm #1																	
	Conduct Pricing Simulations for Algorithm #2																	
	Conduct Pricing Simulations for Algorithm #3																	
Topic 6: Computer Application	Create Basic Computer Application for File Manipulation																	
	Implement Demand Forecasting Models in Computer Application																	
	Implement Pricing Algorithms in Computer Application																	
	Design the Computer Application Interface																	
Topic 7: Report Writing	Write Abstract																	
	Write Introduction																	
	Provide Literature Review																	
	Describe Demand Forecasting Models																	
	Detail Conducted Analysis on Demand Forecasting Models																	
	Evaluate Best Demand Forecasting Model																	
	Describe Pricing Algorithms																	
	Detail Conducted Simulation with Pricing Algorithms																	
	Evaluate Best Pricing Algorithm																	
	Describe Python Computer Application																	
	Write Limitations																	
	Write Conclusion																	

Semester Two Project Plan:

Topic	Activity		Semester 2												
		Date	01/01/24	08/01/24	15/01/24	22/01/24	29/01/24	05/02/24	12/02/24	19/02/24	26/02/24	04/03/24	11/03/24	18/03/24	25/03/24
		Week	Week 17	Week 18	Week 19	Week 20	Week 21	Week 22	Week 23	Week 24	Week 25	Week 26	Week 27	Week 28	Week 29
Topic 1: Planning	Project Ideation														
	Finding Supervisor														
	Conducting Research														
	Write Project Proposal Plan														
	Submit Project Proposal Plan														
Topic 2: Pre-Processing	Data Wrangling														
	Data Cleaning														
	Data Processing														
Topic 3: Demand Model Building	Implement LSTM model in Python														
	Implement GRU model in Python														
	Implement ARIMA model in Python														
	Implement TBATS model in Python														
	Run Analysis on Historical Data														
Topic 4: GitLab	Upload to Gitlab														
Topic 5: Pricing Algorithms	Describe Pricing Algorithms														
	Conduct Pricing Simulations for Algorithm #1														
	Conduct Pricing Simulations for Algorithm #2														
	Conduct Pricing Simulations for Algorithm #3														
Topic 6: Computer Application	Create Basic Computer Application for File Manipulation														
	Implement Demand Forecasting Models in Computer Application														
	Implement Pricing Algorithms in Computer Application														
	Design the Computer Application Interface														
Topic 7: Report Writing	Write Abstract														
	Write Introduction														
	Provide Literature Review														
	Describe Demand Forecasting Models														
	Detail Conducted Analysis on Demand Forecasting Models														
	Evaluate Best Demand Forecasting Model														
	Describe Pricing Algorithms														
	Detail Conducted Simulation with Pricing Algorithms														
	Evaluate Best Pricing Algorithm														
	Describe Python Computer Application														
	Write Limitations														
	Write Conclusion														

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