Price Profile Computer Application for EV Charging Stations

Krzysztof Baran and Xi Zhang

Dublin City University, Dublin, Ireland

Abstract. This project aims to develop data-driven strategies for optimising management of electric vehicle (EV) charging stations. Regression models such as SARIMA (seasonal auto-regressive integrated moving average), LSTM (long short-term memory), GRU (gated recurrent unit) and TBATS (trigonometric seasonality, Box-Cox transformation, ARMA errors, trend and seasonal components) are constructed to forecast demand of an EV charging station based on past demand data. The models are analysed on accuracy and execution time to determine viability in deploying them in applications. In addition, two algorithms for demand-proportional pricing of electricity at EV charging stations were proposed, denoted as range pricing and percentile pricing. The pricing methods are compared with traditional flat and time of use rates to determine their financial performance and demand-proportionality. Finally, a Python computer application is presented, allowing for exploitation of the aforementioned demand forecasting models and demand-proportional pricing methods by EV charging station analysts.

Keywords: EV Demand Forecasting · Demand-Proportional Pricing

1 Introduction

As more EVs appear in cities, the demand for charging stations is also increasing [1]. Unlike when charging conventional internal combustion engine vehicles, EVs must be charged at least for 15 minutes due to the battery characteristics [2]. This is most often done either at work or at home [3] which is the most convenient and cheapest option [4], largely due to cheaper electricity tariffs at night [5] but also due to easy access and flexibility of charging time [6]. The frequency of EV charging depends on the journey planned and is rarely daily [7]. Charging demand fluctuates from hour to hour, day to day [8] and season to season [9], which complicates the utilisation and management of charging facilities.

Public charging stations available can be classified into slow-charging or fast-charging stations [10]. Costs that electricity suppliers charge EV charging stations include fixed monthly grid integration charges, peak demand charges, non-coincident demand charges and finally volumetric energy charges, of which peak demand charges are the most significant [11]. One way to reduce these charges is by encouraging charging off-peak hours. Where scheduling control is not feasible, a dynamic pricing algorithm could be implemented, providing cheaper charging during off-peak hours and more expensive charging during peak hours [12,13].

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 [14] and easily, but they also want to be able to access these services at a reasonable price [15]. With this in mind, an accurate demand forecasting model and a competitive pricing method are particularly important. With accurate forecasting of charging station demand, EV charging stations can better manage and allocate resources [16], 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 EV charging as well as provide easy to use computer applications for analysts to implement these methods is both a challenge and an area worth exploring.

2 Literature Review

The traditional approaches for modelling electricity demand time series is using ARIMA or SARIMA. Choi et al. [17] forecasted EV charging demand for Korean regions using ARIMA, ARIMAX, ARIMA-GARCH, ARIMAX-GARCH, SARIMA and SARIMAX. Accordingly, SARIMA was included in our comparative analysis of forecasting models. Recently, machine learning models have also been used for forecasting demand. Kim et al. [18] applied different time series and machine learning models to forecast EV charging demand and compared their performance. These models were ARIMA, artificial neural networks (ANN), long short-term memory (LSTM) and TBATS. 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 that study, it was decided to also include LSTM and TBATS models in this study's comparative analysis. Zheng et al. [19] conducted short-term load forecasting using EMD-LSTM neural networks with a Xgboost algorithm for feature importance evaluation. Zhu et al. [20] 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, GRU was chosen as the final model featured in the comparative analysis.

Although less common, modelling electricity demand is also done using ensemble models, hybrid models and probabilistic models. Gómez-Quiles et al. [21] created an ensemble model composed of ARIMA, GARCH and PSF algorithms and applied it to forecasting EV power consumption in Spain. Dokur et al. [22] 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. [23] applied Edit Distance to the domain of power load prediction to forecast the short-term load of EV charging stations. Guenoupkati et al. [24] 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.

Profit optimisation strategies for EV charging stations may involve scheduling control or in other words fluctuating the rate of charging. Guo et al. [25] 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. [26] 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.

Limmer [27] surveyed the literature concerning pricing methods for EV charging currently implemented in the United States of America. These included flat time-based rates ($/min), flat usage-based fees ($/kWh), session-based charges (fixed price per charging session), time-of-use (varying tariff depending on when energy is consumed relative to peak-time) and possible additional charges such as an idle charging fee. In this study, the flat energy and time-of-use rates are considered as baseline pricing methods. The prices for the baselines were decided by looking up California EV charging stations' rates on Chargepoint.com. It was determined that 23 cents per kWh for a flat energy rate [28] and 25 cents between 8 am and 9 pm and 20 cents at other times for a time-of-use rate [29] are reasonable baselines.

Several ethical principles relating to electricity pricing have been proposed over time. Bonbright's "Principles of Public Utility Rates" [30] is a work that influenced policy makers including California Public Utilities Commission (CPUC) and its "Electric Rate Design Principles and Demand Flexibility Design Principles" [31] 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" [32]. 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 in advance and logical for users so that they could plan their future use.

3 Methodology

3.1 Data Preparation

The data used in this study comes from the City of Palo Alto in California [33]. The open dataset contains information on EV charges at local stations done between July 2011 and December 2020. Every charge record contains information such as station name, beginning and end times of charging and total energy used. Stations were grouped into station clusters if they had a similar station name and address. The quality of the dataset was examined and issues cleaned. To understand the data's distribution, the dataset was processed using Pig and queried using Hive scripts. Queries included counting the number of charges at each station and station cluster as well as finding the time when data recording began and ended at each station cluster. Python was used to process the data containing charge records at each station into a dataset for each station cluster containing total hourly demand between the earliest and latest times found using Hive.

3.2 Demand Forecasting Models

In our study, we used four algorithms and a baseline to forecast the EV charging demand. They are described below.

SARIMA is a time series forecasting model which models the future values of a variable based on its past values. It has been proposed by Box et al. [34]. The model contains seasonal, differential, autoregressive and moving average parts. Seasonal component allows for modelling cyclical time series such as hourly demand at EV stations. Differential component ensures that the time series is stationary (has consistent mean and variance). Autoregressive component models the demand variable using a linear combination of past values. Moving average component models the demand variable using past forecast errors. In this study, SARIMA parameters were chosen to be $(p = 0, d = 0, q = 0), (P = 1, D = 1, Q = 1)_{S=24}$ to account for the daily cycle in an EV demand time series.

LSTM is a machine learning algorithm that is suitable for modelling series and has been proposed by Hochreiter et al. [35]. It is a recurrent neural network model which contains a cell state as well as 'forget', 'input' and 'output' gates to control how input variables are used to predict the target. In this study, the feature variables are past demand values and their hour of day while the target to predict is the next demand value. After each prediction, the input values are updated with the prediction and the oldest value is dropped. In addition, we have bounded the predictions to be no larger than maximum demand in training data and no smaller than zero. The number of past values considered is the 'look_back' hyperparameter, which together with the 'nodes_per_layer' hyperparameter, were empirically tuned to 48 and 64 respectively. The model predicts using one hidden layer, 50 'epochs', and a 'batch_size' of 16.

GRU is a variation of the LSTM model and was proposed by Cho et al. [36]. It may contain less parameters than LSTM since it contains only two gates: 'update' and 'reset' gates. In this study, we model demand using GRU in the same way as outlined for LSTM. However, the 'look_back' and 'nodes_per_layer' hyperparameters were empirically tuned to 24 and 128 respectively.

TBATS is a model suitable for modelling time series with multiple seasonalities and has been proposed by De Livera et al. [37]. Future values of a variable are modelled based on its transformed past values. TBATS employs multiple types of transformations which is useful if the target variable is not linearly-dependent on its past values. This study uses a Python implementation which automatically chooses the transformations and hyperparameters based on the training data. Seasonalities specified are 24 and 168, representing the daily and weekly seasonalities which may be present in an EV demand time series.

Baseline model calculates the mean and standard deviation of the demand values in the training data and always predicts a random number in the interval of mean plus standard deviation and mean minus standard deviation. The model has a random seed of 1 to allow for reproducing results.

3.3 Pricing Methods

We developed two pricing methods called range pricing and percentile pricing. They are described below.

Range Pricing is introduced in this study as a demand-proportional pricing method of electricity in a given hour. Given the minimum and maximum values for electricity prices at an EV station and the forecasted demand values, the method may assign a given hour an appropriate price per kWh based on how high the predicted demand for the hour is compared to the maximum demand value of all predictions. The range of predicted demand values is evenly divided into different demand intervals and a specific price is assigned to each interval. Each predicted demand value is categorised into one of the demand intervals and is assigned the corresponding price. This method makes the price of electricity proportional to the demand of consumers in a given hour: the higher the demand, the higher the corresponding price of electricity and vice versa. In this study, the minimum and maximum prices per kWh are set to 20 cents and 25 cents respectively.

Percentile Pricing is also introduced in this study as a demand-proportional pricing method of electricity in a given hour. Given the minimum and maximum values for electricity prices at an EV station and the forecasted demand values, the method may assign a given hour an appropriate price per kWh based on how high the predicted demand for the hour is when converted to a percentile of all predictions.

Equal percentile intervals are calculated to match the number of possible prices. Demand intervals are calculated by finding the predicted demand value at each percentile interval boundary and a specific price is assigned to each demand interval. Each predicted demand value is categorised into one of the demand intervals and is assigned the corresponding price. This method makes the price of electricity proportional to the demand of consumers in a given hour: the higher the demand, the higher the corresponding price of electricity and vice versa. In this study, the minimum and maximum prices per kWh are set to 20 cents and 25 cents respectively.

Flat Energy Rate is a traditional and basic pricing method which always assigns a set price. It does not take into account changes in time or energy demand. In this study, the flat energy rate serves as a baseline and is set to 23 cents per kWh.

Time of Use Rate is traditionally used to alternate electricity rates based on the time of day. It typically sets higher electricity prices during periods of peak demand for electricity and lower prices during periods of low demand to encourage electricity use at that time. The rates at a given hour will remain constant every day no matter the demand fluctuations. In this study the time of use serves as a second baseline and outputs 25 cents per kWh from 8 am to 9 pm (peak hours) and 20 cents per kWh at all other times (off-peak hours).

4 Performance Evaluation

4.1 Set-up for Tests

For every test, ten batches were randomly selected from each station's dataset using a random seed of one. We made sure that these batches did not overlap and did not have total demand equal to zero. As the data was a time series, every batch was split into a training set followed by a test set. For each batch the data was split using three different training methods: 1) the training data was always a two week period; 2) 75-25 split for training and testing; and 3) 50-50 split. The accuracy and execution time tests were run for forecast periods of one, three, seven and fourteen days while the revenue and demand-proportionality tests had periods of one, two, three, seven, fourteen and twenty eight days. In addition to the batch results, the maximum, minimum, mean and standard deviation of the ten batch tests were also recorded.

4.2 Metrics

The metrics for accuracy were normalised root mean squared error and normalised mean absolute error since different models were tested and batches had varying lengths. The metric for demand-proportionality of pricing methods was Pearson Correlation Coefficient. For measuring execution time, a timer in the Python script was started after the batches were extracted but before the model was defined or the dataset was further processed for the model. The timer was stopped once predictions were completed and the number of seconds was recorded.

4.3 Results

Table 1. Demand Models Comparison

Model	NMAE	NRMSE	Time (s)
SARIMA	0.788	1.105	0.926
BASELINE	1.161	1.468	0.001
GRU	1.827	2.186	15.047
LSTM	1.983	2.302	15.025
TBATS	94717.229	139330.91	21.249

Table 2. Training Methods Comparison

Training Method	NMAE	NRMSE	Time (s)
14 Days Training	1.106	1.369	10.14
Training:Testing = 50:50	1.191	1.435	8.831
Training:Testing = 75:25	1.195	1.489	12.378

Table 3. Forecast Periods Comparison

Forecast Period	NMAE	NRMSE	Time (s)
1 Day	1.234	1.512	7.734
3 Days	1.160	1.418	6.859
7 Days	1.107	1.392	10.466
14 Days	1.156	1.404	16.739

Table 4. Pricing Methods Comparison

Pricing Method	1 Day	2 Days	3 Days	7 Days	14 Days	28 Days	Average Revenue	Pearson Correlation Coefficient
Flat Energy	24.13	50.68	78.37	183.36	371.18	754.26	243.66	0
Time of Use	25.74	53.86	83.25	194.48	393.4	799.43	258.36	0.555
Percentile	25.53	53.6	82.92	193.96	392.58	798.03	257.77	0.918
Range	24.86	51.73	79.77	184.61	371.9	753.11	244.33	0.982

5 Discussion

SARIMA is the model with the best mean accuracy performance. It also has the shortest execution time when not counting the random number generating baseline model. On the other hand, TBATS has extremely high mean NMAE and NRMSE due to its numerous unnaturally high predictions. It is possible that an exponentially increasing model was generated in certain tests. This makes the model impractical in deploying in the application. Although GRU and LSTM seem to have worse performance than the baseline, their predictions still model demand to a useful degree.

Training the models on fourteen days of data leads to the best accuracy performance although the training methods have almost identical scores. Execution time is shortest on average when the training and forecast durations are equal.

The differences between accuracies of different forecast periods are negligible. It can be concluded that accuracy does not vary with forecast period. However, execution time in general increases with forecast period.

Time-of-use represents the most profitable method but percentile pricing's revenue optimisation compares well. It should be noted that percentile pricing's correlation is twice as high and the increased demand-proportionality could in theory increase customer turnover and reduce grid costs. Range pricing has the highest demand-proportionality but its financial performance is not much higher than of the flat energy rate.

6 Computer Application

In order to provide an accessible way to predict EV charging demand and implement demand-proportional pricing strategies, a computer application was developed. The Python library Tkinter was used to structure the application into a hierarchy of windows. The application was designed to use historical data to predict future demand and then set a reasonable demand-proportional price for each hour using either range pricing or percentile pricing. SARIMA, GRU and LSTM were implemented in the application since they were the best-performing demand models in our analysis. To run the application, the requirements from requirements.txt need to be imported and the main.py script executed. Once the user selects parameters and the prediction is completed, a dashboard is generated and the user may download the results.

Specifications Page allows the user to select parameters such as the demand model and pricing method to use, the forecast duration and the price interval of desired prices. The application implements validation mechanisms and warns the user if anything is amiss. A progress bar appears once the predicting begins.

Dashboard Page allows the user to analyse a variety of charts and export them. The charts display historical and forecasted demand by day and by hour as well as forecasted revenue by day and a visualisation of the generated price profile's proportionality to demand. Moreover, the same data may be downloaded by the user into an Excel file. Total forecasted revenue and demand is also displayed.

About Page provides the user with detailed instructions for using the application, introduces the application's purpose, explains the available methods and presents the authors.

Help Page provides detailed instructions for using the application. Questions answered relate to uploading data and its necessary format, selecting parameters to pass the validation checks, using the dashboard functionalities, navigating between pages and exiting the application.

Home Page is the start-up page. On this page the user may select which page they want to navigate to or whether they want to exit the application instead.

7 Limitations

The data set used in this study recorded EV charges done exclusively in the city of Palo Alto, USA. The charging trends observed in American data may not be the same as in other countries. The data set contained only eight charging station clusters and all represented public urban charging stations. These misrepresentations may limit the general applicability of the findings. On another note, due to limited resources we could not set up an experiment to collect data on EV stations implementing the range and percentile pricing methods. This limited our analysis of their impact on revenue, customer behaviour and balancing demand through the day.

Due to limited computational resources our analysis was limited to running ten batches in each category and forecasting for periods longer than fourteen days was not done. Although hyperparameter tuning was attempted, it is possible more optimal hyperparameters were not explored.

The application developed in this study relies on Python and Tkinter technologies. Their capabilities are relatively limited in terms of enabling more advanced interactions and visuals. Technologies such as JavaScript, HTML and CSS could support a more sophisticated front-end. Designing a cloud-computing back-end would allow for faster prediction generations. The set-up of the application may be cumbersome and the distribution limited since the application can only be run locally and not on the web.

The time series analysing models in this study simply regress over past data. They do not take into account other factors and so their accuracy worsens the further ahead predictions are made. The EV market and associated charging demand are influenced by a variety of external factors, such as economic conditions, policy changes, technological innovations, weather and changing consumer behaviour. As these factors change, patterns in historical data may no longer apply, leading to a decline in the accuracy of model predictions. Furthermore, technological innovations such as increasing battery storage capacity or increasing charging speed, may disturb patterns of EV charging demand.

8 Challenges

Executing numerous GRU, LSTM and TBATS models was heavily computationally and time-consuming. As our application would be run on a personal computer, we could not avail of cloud computing when testing execution time. Instead, we employed numerous university computers to run different scripts simultaneously.

Designing an algorithm for predicting EV charging demand using GRU and LSTM posed challenges. Unlike with SARIMA, regressing on past values alone was not working. It was necessary to consider time of day as a feature so that the predictions would not plateau.

9 Future Work

Research involving a comparative analysis of range and percentile pricing methods applied in practice for setting future EV charging stations' prices would shine light on their impact on customer behaviour, revenue gains and EV charging demand balancing. In addition, more machine learning models could be evaluated.

10 Conclusion

The accuracy and execution time analysis results point to SARIMA as the best model for forecasting EV charging demand. The ratio of training to forecast duration does not impact forecasting accuracy. Accuracy of predictions is reliable when forecasting up to fourteen days. The percentile pricing method shows promise as a highly demand-proportional pricing strategy.

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11 Appendix

The application, analysis code, data and visualisations can be found in this repository: https://gitlab.computing.dcu.ie/barank2/2024-ca4021-barank2-zhangx28

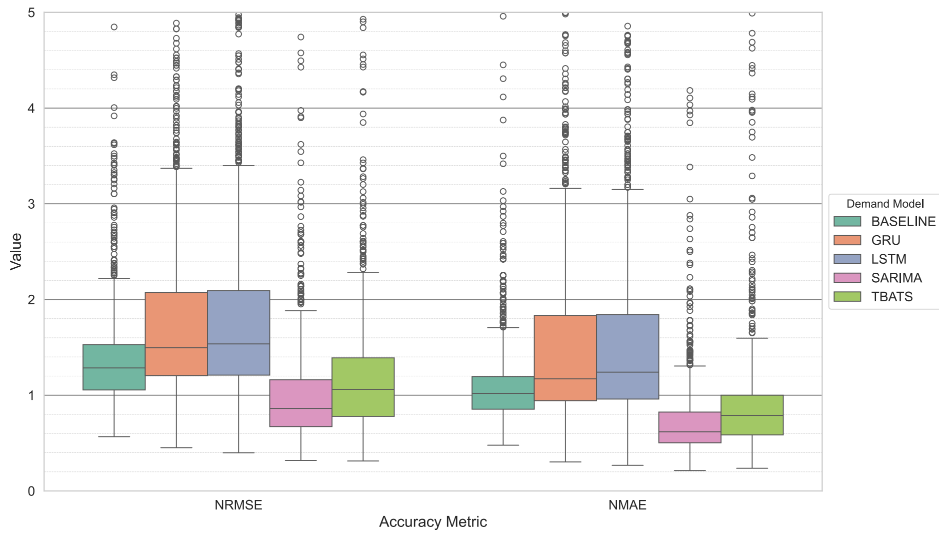

Fig. 1. Accuracy distribution of demand models

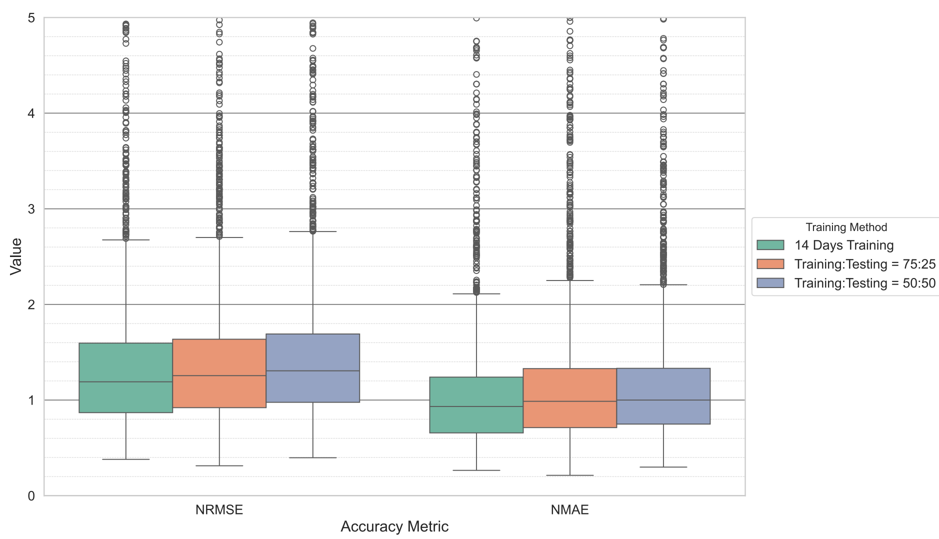

Fig. 2. Accuracy distribution of training methods

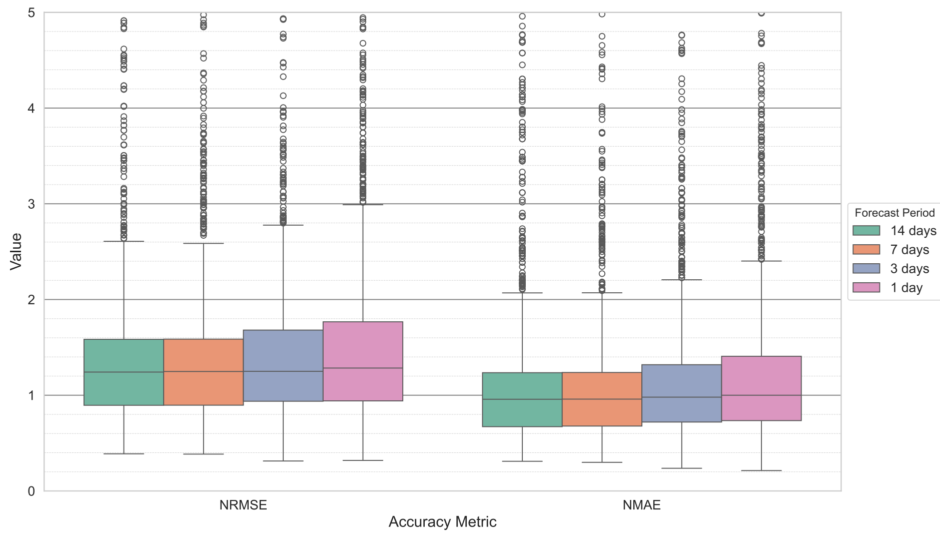

Fig. 3. Accuracy distributions of forecast periods

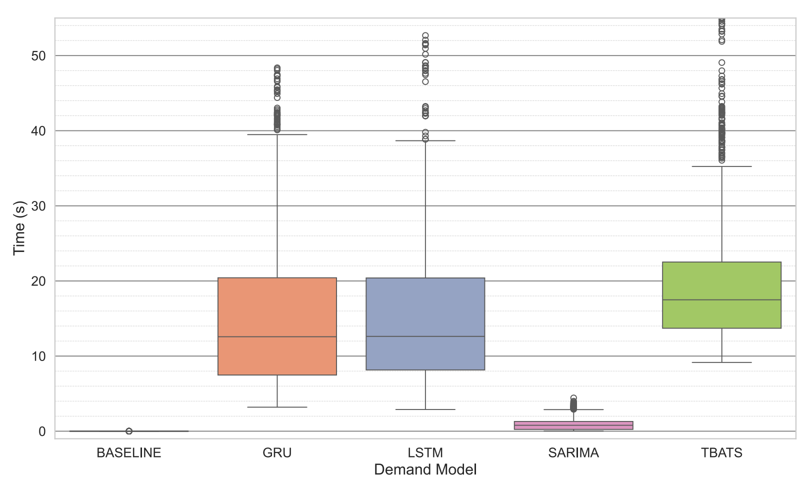

Fig. 4. Execution time distribution of demand models

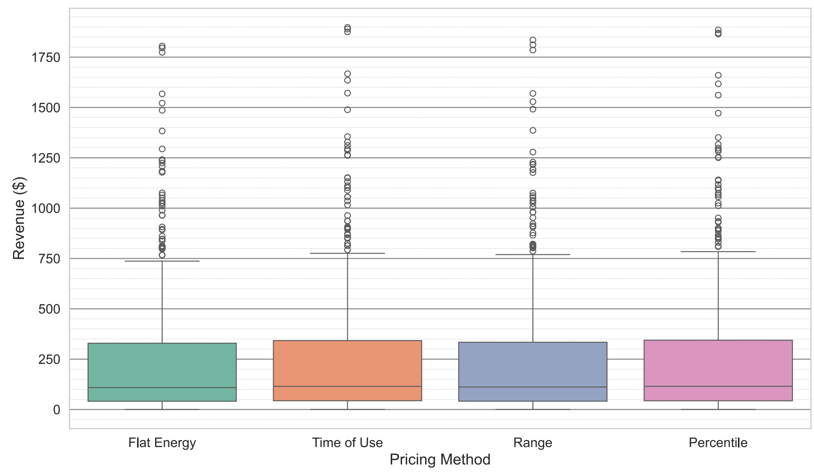

Fig. 5. Revenue distribution of pricing methods

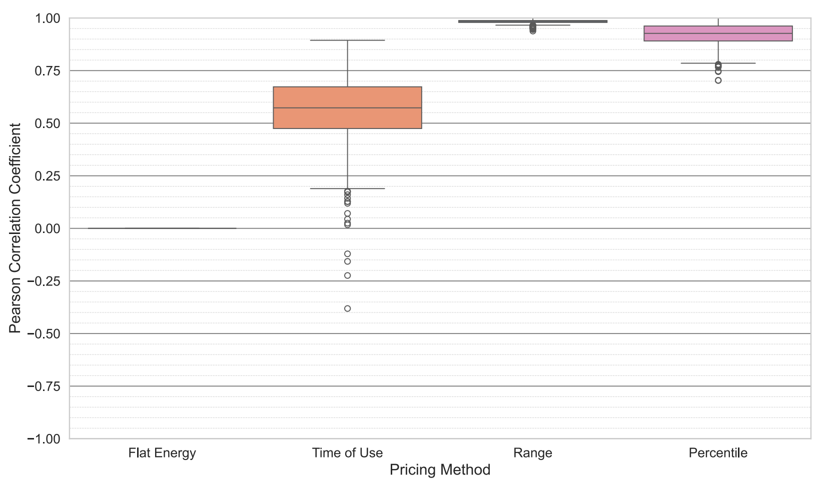

Fig. 6. Demand-proportionality distribution of pricing methods