Learning Based Pricing Strategies for Demand Response

Project Report

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Abstract

This report proposes a learning based optimization methodology for pricing in demand response programs.

Introduction

Demand response is defined as the reduction in demand by the consumers in response to changes in electricity prices or incentives provided by the system operator. Demand response programs lower the cost of electricity in the wholesale and retail market, removes chances of overload and subsequent power failures.

Stackelberg game

In game theory, the stackelberg game is a leader-follower game where the leader considers the follower's response to optimize its strategies. In this paper, the system operator is the leader and the electricity consumers are the followers. In addition to learning the customer behavior and incorporating it in the optimization problem, the SO (system operator) in this model is also penalized for deviating too far from customer preferences (which are learnt).

Problem Formulation

Instead of posting a constant price as an incentive, we build towards a model that would post different prices to different consumers based on how well they perform in the past.

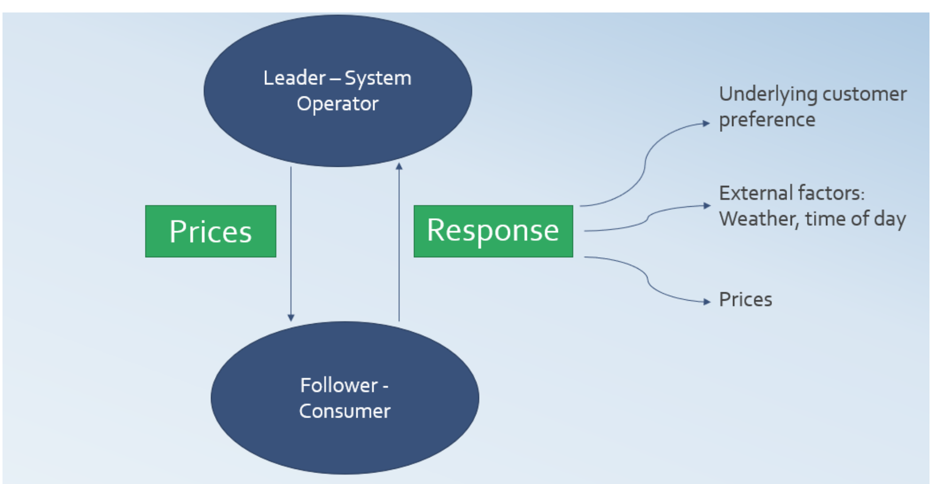


Figure 1: Bilevel optimization: Need for learning

The consumers respond to the prices posted by the leader(SO). This may also depend on some externam factors like weather and time of day. In order for the stackelberg optimization, the SO needs to have this information to optimize both consumer and its utilities and find an equilibrium. This is done by learning customer behavior by using past data and a slew of techniques borrowed from machine learning.

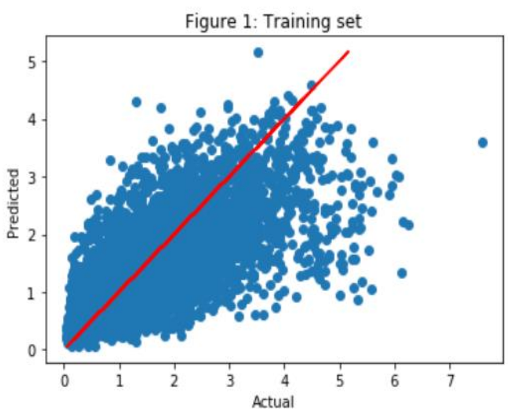
Learning

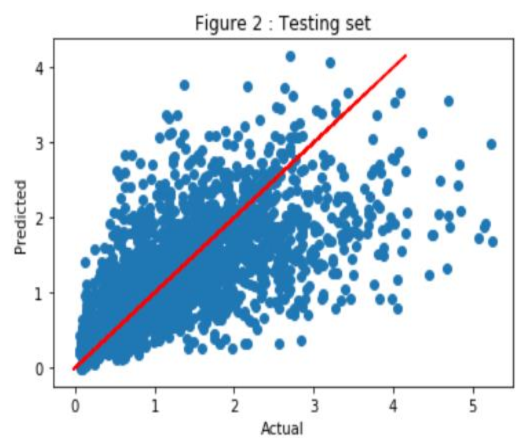
1. **Predicting power consumption**

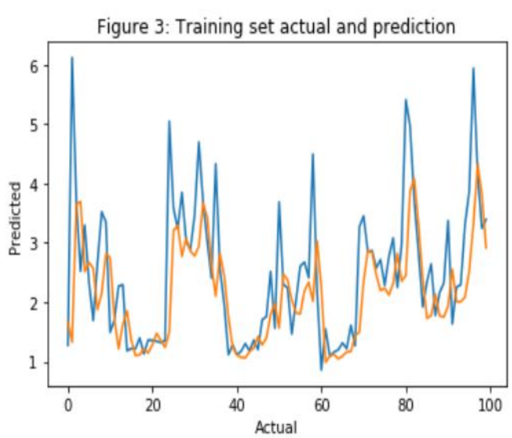
   Support vector regression was used to predict consumer power usage pattern from past data. Data was obtained from the University of Massachusetts dataset which had 3 years power usage data for 114 homes with one-minute intervals. This was converted to one-hour interval since that is the time period considered for posting prices for demand response. The data contains power usage in KWh and weather data associated with each hour. A total of 8000 data points were divided into 5700 for training and 2300 for testing.

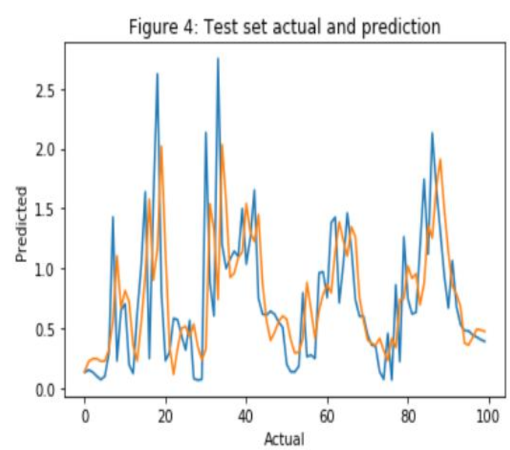
   <u>Results:</u>

   Cross-validation was performed, and results obtained are shown below for one house.









The score on the training set is 0.675055213466 and the score on the test set is 0.788481487599.

2. **Synthetic data generation for demand response**

   10 houses were selected based on the outcome of the results from the previous step and synthetic data was generated for each of them. A ground truth probability of positive response was assigned to each house as shown:

   Probability of positive response: [0.32 0.5 0.31 0.78 0.44 0.84 0.09 0.06 0.12 0.3]

   The data was generated by adding noise and accounting for past performance by assigning the required reduction to be a parameter "m" percentage of the consumers actual usage obtained from the true data. A vector of random m values between 0 and 1 were generated and was assigned to each house based on their past performance.

   The figure below visualizes the data generated for six houses. The graphs show the demand response by using circles to denote positive demand reduction and crosses to denote negative demand reduction. As seen, house number 6 has a very high frequency of reducing demand and house 10 has a low frequency but reduces demand by a high amount every time it does.

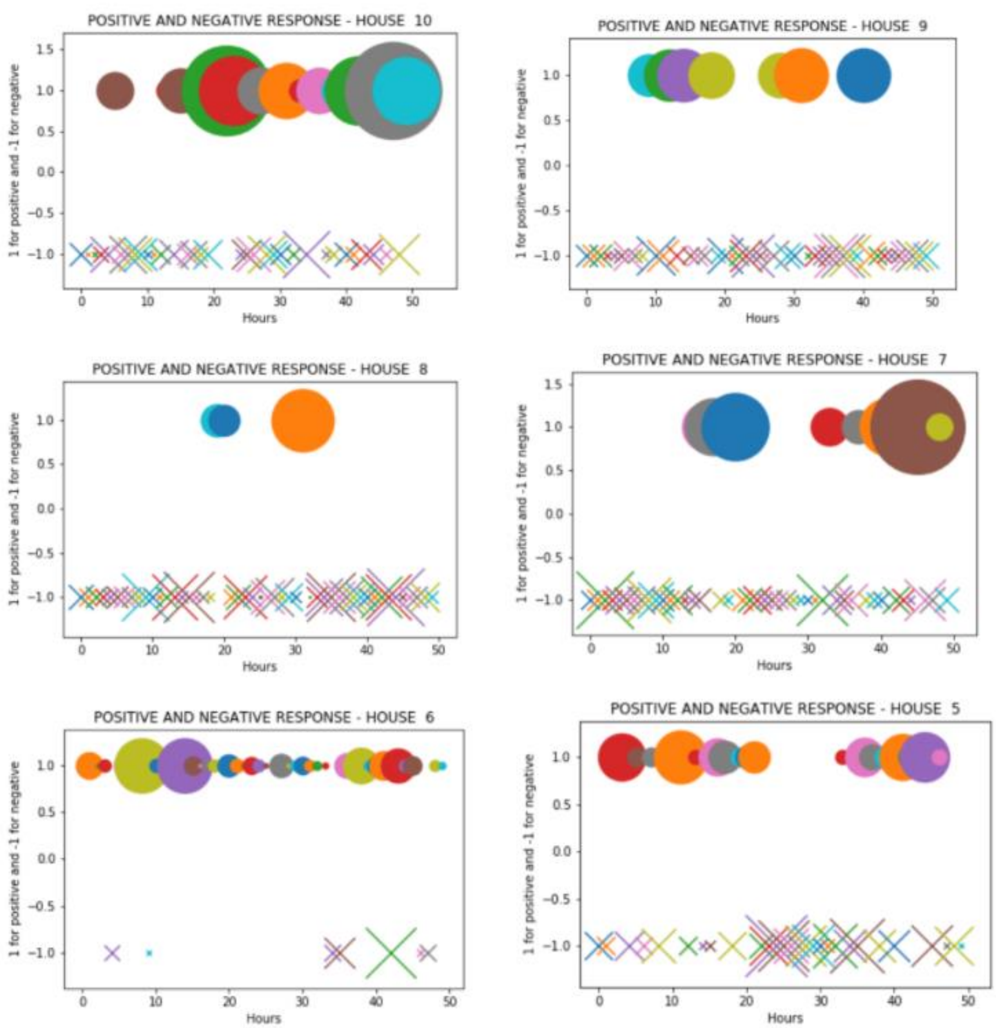


Figure 2: Visualizing synthetic data

3. Probability prediction

A linear model for demand reduction and prices can be learnt from past data. For the purposes of this project, values of prices were generated and fit to the synthetically generated data. Logistic regression was used to generate a probability of positive response using the weather, predicted power (from step 1 using support vector machines) and pricing data. 2300 data points were divided into 1000 training and 1300 testing points.

<u>Results</u>:

Cross-validation was performed, and optimal C value (inverse regularization strength) was chosen. Positive recall is defined as the ability of the algorithm to predict true positives (ability of the SO to predict when customers will reduce power). C was optimized to maximize positive recall. The results obtained are shown below. It is seen that the running average of the predicted probabilities approach the probabilities initially assigned to the customers during synthetic data generation.

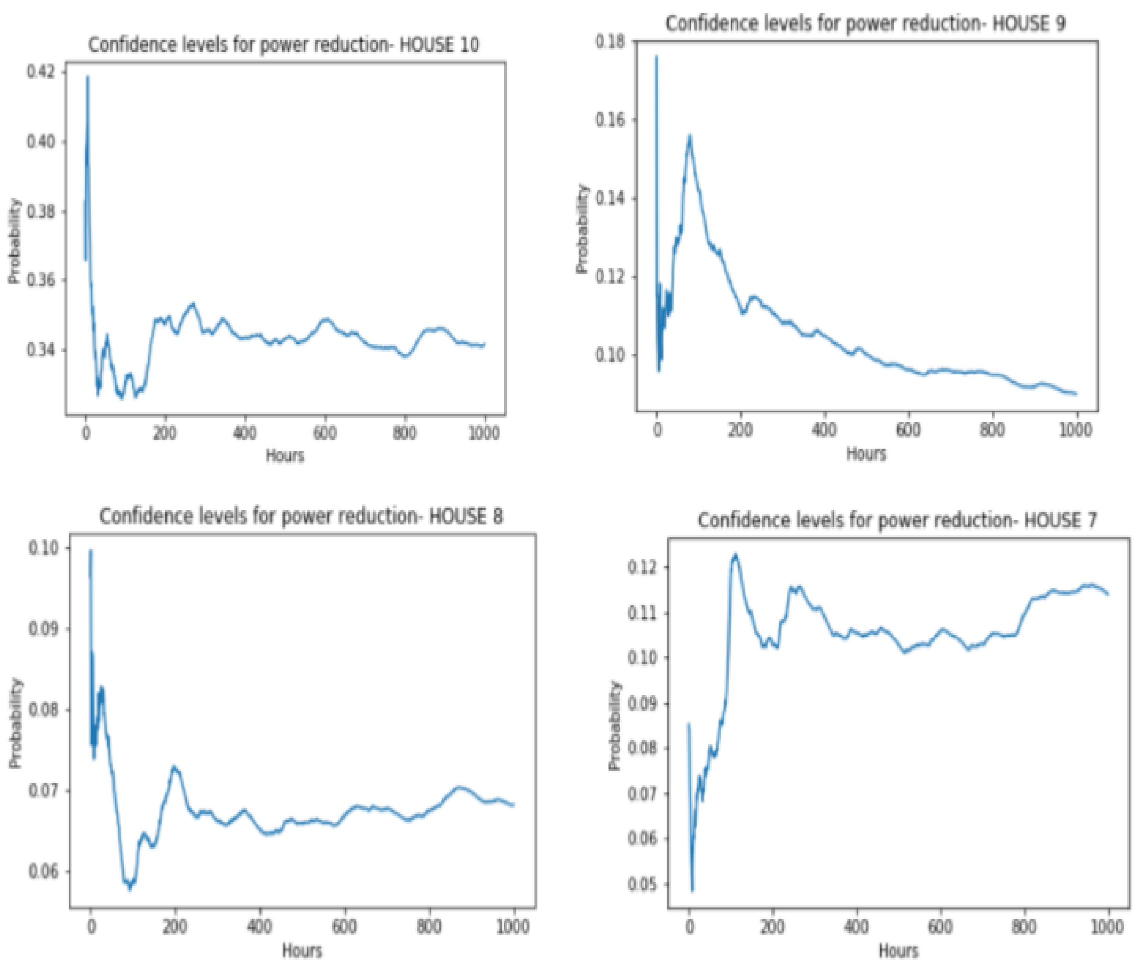


Figure 3: Results of probability prediction

Optimization

Using the data learnt using the above techniques, the system operator optimizes the prices to be posted. The objective function is described below:

$$\min_{\vec{P}} \left\{ \underbrace{(\text{KL divergence} + \text{Over-Estimation})}_{\text{Inconvenience Cost}}*(\text{ICF}) + \underbrace{(\text{cost\_so} + \text{cost\_cust}}_{\text{Monetary Cost}}*(\text{CI}) + \underbrace{\text{prev\_fail}}_{\text{Loss in time t-1}}) \right\}$$

$$\text{Subject to: } \begin{cases} 0 \leq P(i) \leq 1 \\ Dr(i) \leq P(max) \end{cases}$$

1. KL divergence is the difference in predicted probability distributions and actual probability distribution. This is added as the inconvenience cost of the customer.

$$D_{\mathrm{KL}}(P\|Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}$$

2. A linear model between the prices posted and the demand reduction allows calculation of the system operator's belief of what the demand reduction might be. If this exceeds the maximum possible power of a consumer (the predicted power because that is the information available to the system operator) it is added as a cost in the objective function.

3. The system operator's cost is the negative of the savings. Savings is defined as the money saved by the SO due to the demand reduction by the consumers.

$$\text{Normal loss} = (W - R)^* \, Y_{pred}$$

$$\text{DR loss} = (W- R)^*(Y_{pred}\text{- } Dr(pred)) + \sum_{i=1}^{n} P(i)$$

$$\text{Savings} = \text{Normal loss} - \text{DR loss}$$

The wholesale price W = 1.89 $/KWh and retail price R = 0.19 $/KWh.

4. Customer's cost is the negative of the customer's savings. This is the retail price saved because of reduced power usage as well as the payment received in the demand response program.

$$\text{Savings} = R^*\sum_{i=1}^{n}(Ypred - Dr(pred)) + \sum_{i=1}^{n} P(i)$$

5. Prev_fail is a parameter used to penalize the system operator for inaccuracies in predicting customer preference in time t-1. This is added to the objective function in the form of losses incurred in time t-1 and difference between actual and predicted power reduction in time t-1.

$$\text{Prev\_Fail} = Dr(pred) - actual(pred) + Loss(t\text{-}1)$$

6. The factors ICF (inconvenience factor) and CI (customer importance) can be chosen accordingly. Increasing ICF AND CI will reduce the SO's savings and increase customer comfort.

The optimization problem was solved in python using the COBYLA optimizer. The results obtained are shown below:

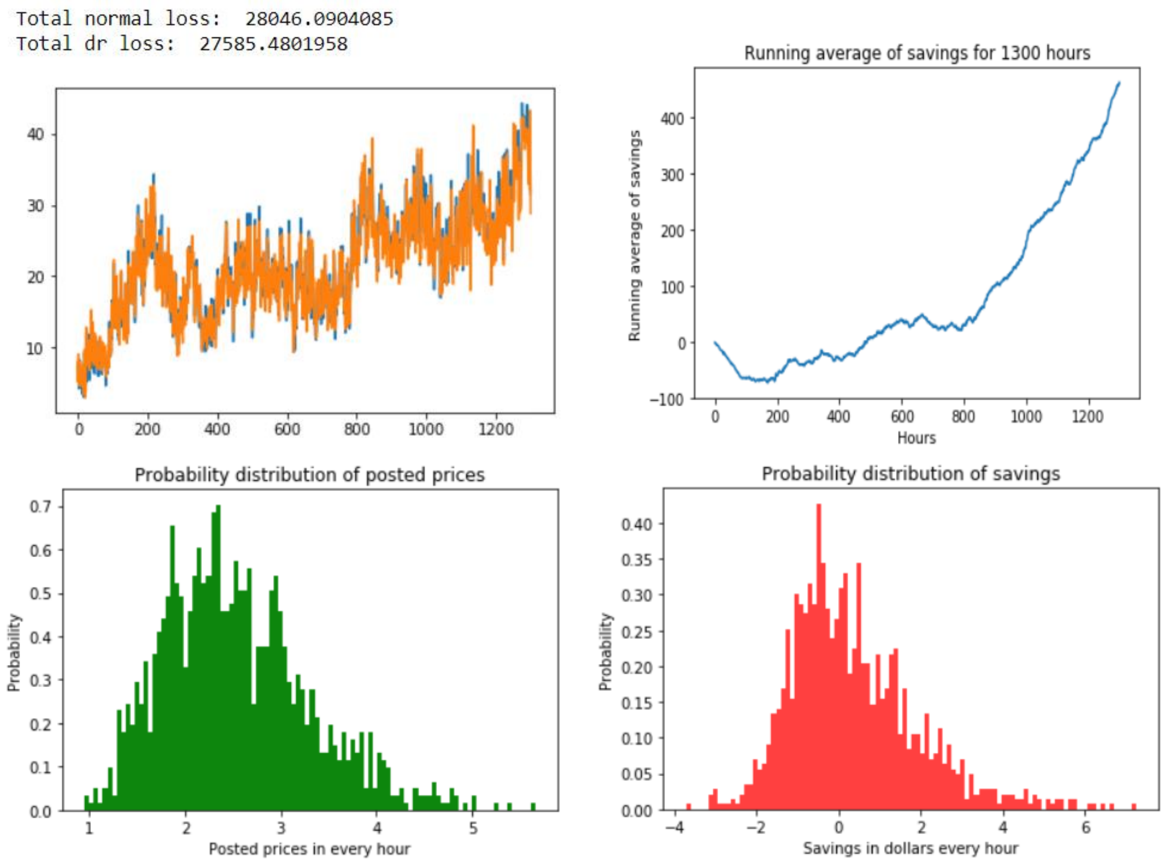
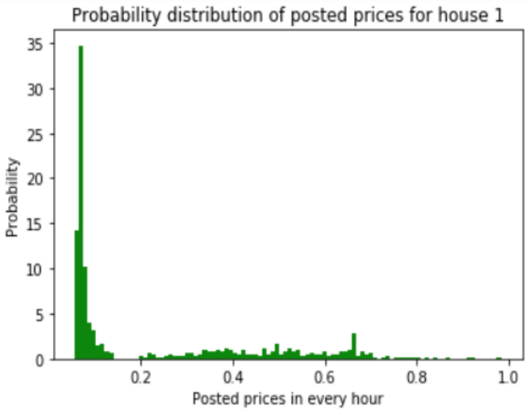


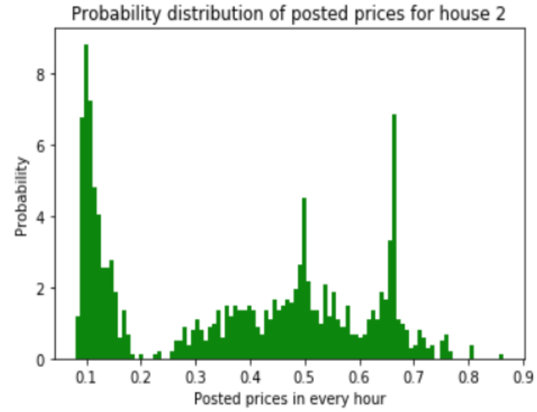
Figure 4: Results of optimization

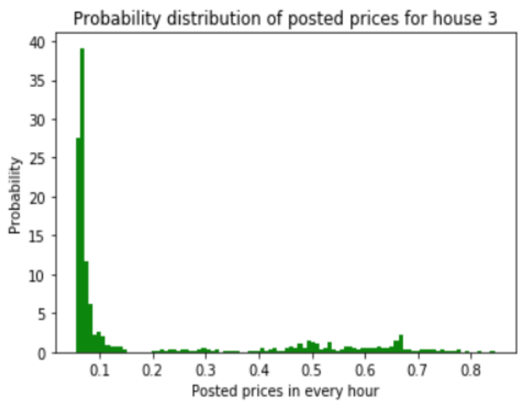
ICF was chosen to be 1 and CI was chosen to be 0.3. With these factors chosen,

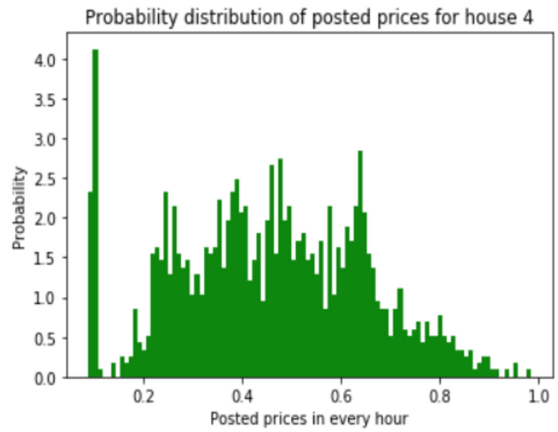
1. The money saved is around 500 dollars (around 2 percent of the losses incurred). This is a hypothetical situation considering two houses, and the numbers would seem more significant if calculated in the actual power market setting.
2. The running average of the savings is plotted on the top right figure. It shows that in the initial 200 hours, the SO incurs losses, after which the SO saves money in the demand response program.
3. The probability distributions of the savings and the total posted prices are also shown. On average, the posted prices in every instance is 2-3 dollars in total for all the customers.

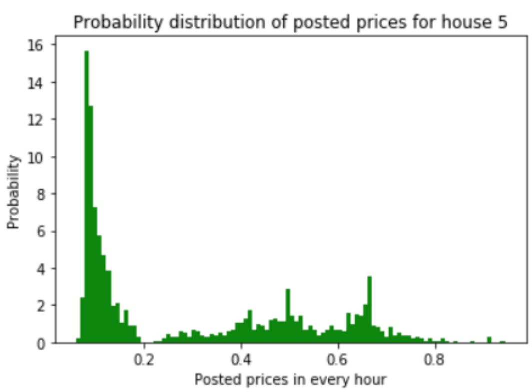
The probability distribution of the posted prices for each of the customers is shown below. It is observed that the system operator learns the underlying probabilities of positive response and accordingly optimizes its pricing strategies.

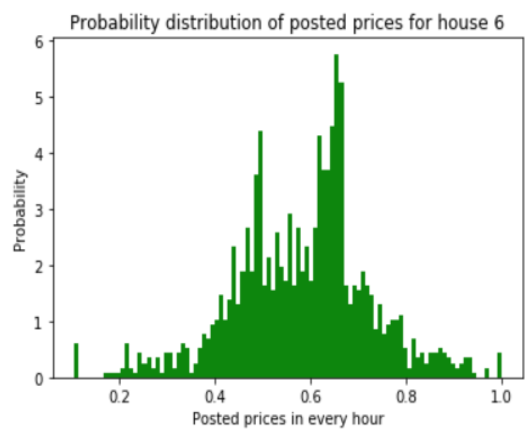

Probability distribution of posted prices for house 1
Probability
Posted prices in every hour

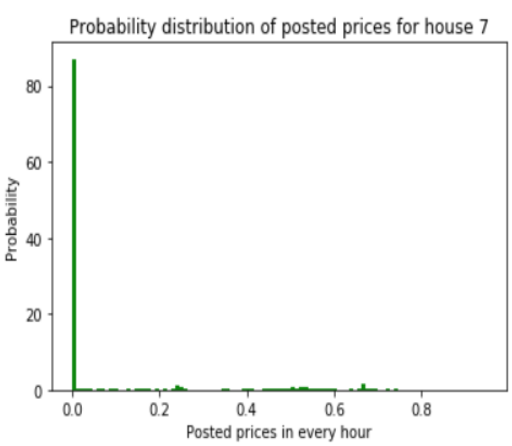

Probability distribution of posted prices for house 2
Probability
Posted prices in every hour

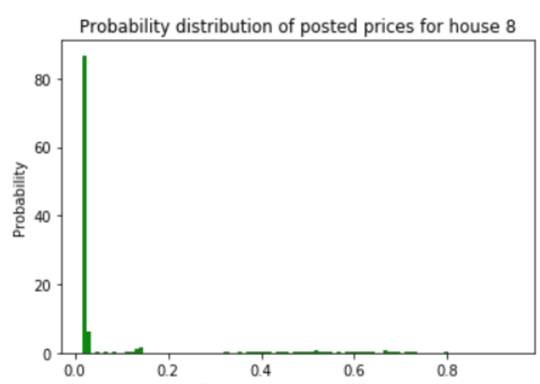

Probability distribution of posted prices for house 3
Probability
Posted prices in every hour

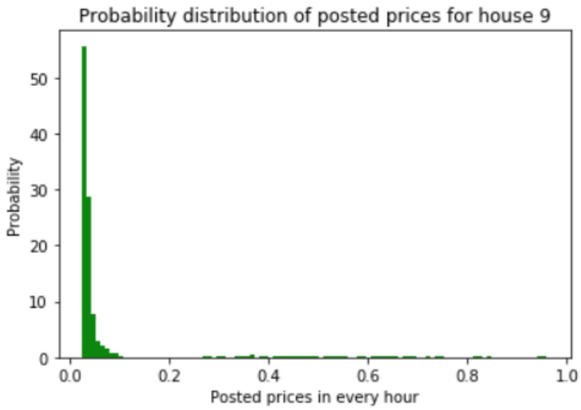

Probability distribution of posted prices for house 4
Probability
Posted prices in every hour

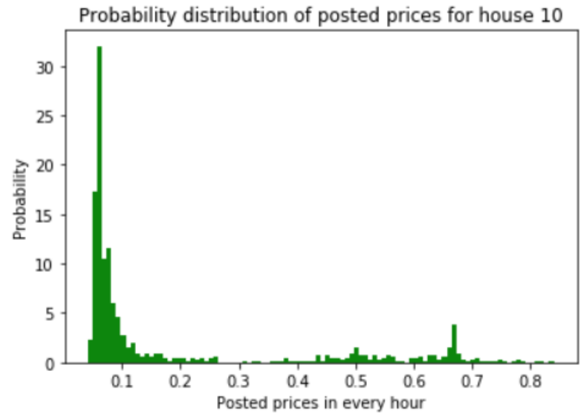

Probability distribution of posted prices for house 5
Probability
Posted prices in every hour


Probability distribution of posted prices for house 6
Probability
Posted prices in every hour


Probability distribution of posted prices for house 7
Probability
Posted prices in every hour


Probability distribution of posted prices for house 8
Probability
Posted prices in every hour





From the probability distributions, house 6 (with maximum probability of positive response) is usually posted with a higher price than other houses. The other consumers are posted with high prices very rarely due to their poor past performances which the system operator considers during optimization.

Conclusion

Thus, a learning based pricing strategy was proposed in this paper instead of using constant prices. It was shown that savings could be made when customers are payed based on their past performance. The learning algorithm can also adapt to changing customer preferences with time.

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