An Application of Machine Learning for a Smart Grid Resource Allocation Problem

Yingying Zheng
Siddharth Suryanarayanan
Anthony A. Maciejewski
Howard Jay Siegel
Dept. of Electrical and Computer Engineering
Colorado State University
Fort Collins, CO 80523, USA

Timothy M. Hansen
Dept. of Electrical Engineering and Computer Science
South Dakota State University
Brookings, SD 57007, USA

Berk Celik
Laboratoire LAPLACE
Université de Toulouse
Toulouse, 31077, France

***Abstract*—The ability to predict aggregator profits is important in the design of an efficient aggregator-based residential demand response (DR) system. In this paper, supervised machine learning models are designed based on historical data to investigate the influence of customer schedulable loads and the forecasted daily electricity price profile on aggregator profits. The k-nearest neighbors (KNN) and Gaussian process regression (GPR) are chosen because of their consistent performance and high accuracy compared to other machine learning (ML) classification and regression algorithms. Our study demonstrates the classification model is an effective approach to identify the set of schedulable loads that may yield high aggregator profits and the regression model may enable awareness of day-ahead aggregator profits.**

***Index Terms*—Aggregator, demand response, machine learning, schedulable loads, Smart Grid.**

I. Introduction

Smart Grids allow the bidirectional interaction between load serving entities (e.g., utilities) and their customers. The distribution system is equipped with advanced metering infrastructure (AMI), including smart meters, to allow real-time monitoring of energy consumption as well as the capacity for participants to set their electricity demand (or supply) in response to price or other signals from the bulk electricity system [1]. It is challenging for the bulk electricity market and its participants to directly communicate with and control a multitude of distribution level consumers for influencing the electricity demand. Hence, a for-profit third-party market entitythe aggregatoris emerging in the power industry to bridge the gap between the bulk electricity market and the distribution level energy consumers, thus providing an opportunity for end-to-end deregulation of the electricity infrastructure.

Aggregators are no longer merely theoretical entities; for instance, in California, USA, aggregators wishing to solicit and serve utility bundled customers must register with the California Public Utilities Commission (CPUC) [3]. Table I lists some aggregators that provide service to residential or small commercial customers with a valid CPUC registration in the service areas of the three major utilities in California (PG&E, SCE, and SDG&E). The objectives of the aggregator may include: (a) to maximize its own revenue; (b) to shave the peak demand; and (c) to provide energy bill savings to the participating end users. The aggregator acts as a retailer that buys electrical energy from the bulk electricity market based on the forecast of day-ahead prices [2]. A contractual agreement between the spot market and aggregator details the exchange of money for the aggregator action to defer demand during pre-identified hours. The aggregator expects to achieve its promised delivery to the contract with the bulk electricity market for demand deferral. This is achieved via the provision of incentives to a large group of electricity consumersthus, delivering a widespread demand response (DR) program among distribution customers, especially residential end users. The literature in this area includes studies considering incentive-based programs for the aggregator such as the energy bidding pricing model [4]–[8].

TABLE I
RESIDENTIAL AGGREGATORS IN CALIFORNIA [3]

Aggregator	PG&E	SCE	SDG&E
EnergyHub, Inc.	✓	✓	
OhmConnect, Inc	✓	✓	✓
Olivine, Inc.	✓	✓	✓
Chai, Inc.		✓	
eMotorWerks, Inc.	✓	✓	✓
Sunrun, Inc.	✓	✓	

Previously, we developed an aggregator-based residential DR approach using a genetic algorithm (GA) to maximize the aggregator profits (AP) [9]. The proposed Smart Grid resource allocation (SGRA) considered 5,555 customer households with of probabilistic profiles of approximately 208,000 schedulable and base loads that were simulated over a time horizon of 24

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hours.

In the SGRA approach, the aggregator incentivizes users to modify their electricity consumption profile by providing a day-ahead customer incentive price (CIP) in lieu of the real-time price (RTP) offered by the local utility company. The customers can potentially examine the tradeoff between savings in electricity bills by participating in the new DR program with the aggregator versus the discomfort from having to change their appliance usage profile before making decisions (at device level resolution) to enter into a daily contract with the aggregator; the default option for these customers is the use of electricity from the utility billed at the RTP rate. The results demonstrate that the SGRA CIP is, in general, better than the utility RTP. Hence, the customers achieve savings in their electricity bills by participating in the aggregators DR program. The savings are based on the customer flexibility and number of participating loads. Concomitantly, the aggregator can attain a profit by selling negative peak load to the spot market.

One of the biggest challenges for evaluating and predicting the aggregator performance is handling the massive amount of data that is expected to be collected from stochastic asset inputs, customer behaviors, and dynamic utility prices. The ability to handle massive data and provide accurate prediction makes machine learning (ML) suitable for this Smart Grid application. ML refers to a large class of algorithms that infers patterns from data to make predictions on outputs. There are two main types of ML algorithms that are designed to achieve the same general goals: supervised and unsupervised. Unsupervised methods find a pattern between input variables without referring to a specific outcome; supervised methods typically attempt to classify or predict a response based on known outputs for a set of inputs [10].

The literature on the application of ML for the Smart Gird is extensive and growing; providing an exhaustive listing of such applications is out of scope of this paper, but methods like artificial neural networks [11], fuzzy logic [12], and support vector machines [13] are popular in their application to this realm. Given that the field of research in aggregators is nascent, there are not many examples of the application of ML to AP forecasting, although many studies have focused on predicting energy consumption using ML techniques [14].

Here, we aim to build both classification and regression models by using the data from our previous studies on SGRA simulations to predict AP. Our previous research relied on the use of high-performance computing (HPC) and parallel algorithms to deduce AP, involving dedicated computational platforms. Such specialized and cost prohibitive assets may not be widely available; thus, the motivation to use the data generated from the HPC-based simulations to develop metadata representations of the AP to reduce computational requirements. The contributions of this work are as follows: (a) design a ML model to obtain relationships between AP and customer loads; and (b) understand the influence of forecasting utility energy and spot market prices on AP. We add the caveat lector that the methods and models developed here are not intended to be generic for all systems; rather, we endeavor to provide a framework of the use of ML for this particular type of application. Results presented in this paper are specific to the data, system, algorithms, and hardware used.

The remainder of this paper is organized as follows. Section II briefly revisits the SGRA problem. The use of the ML algorithms is described in Section III. Section IV presents the simulation results and Section V concludes.

II. SGRA Problem

A. Overview

Because the ML models are trained using the data from the SGRA approach from [9], a brief description of the SGRA problem is presented here. The SGRA problem is designed as an aggregator profit maximization algorithm with the intention of peak load shifting by the provision of a competitive alternative to the utility price for electricity (i.e., CIP). To generate the CIP, a heuristic algorithm (i.e., GA) processes the inputs received from the customers on the loads available for scheduling, and other pertinent information like the forecast price of electricity in the day-ahead from the utility and from the bulk electricity market. The list of inputs to the SGRA is shown in Table II. The mathematical details of the SGRA problem are described in detail in [9].

TABLE II
INPUT INFORMATION TO DETERMINE CIP

customer schedulable loads	Forecast pricing data
runtime duration (in 15-minute intervals)	utility pricing
average power rating	spot market pricing
customer originally start time	
availability window start time	
availability window length	
flexibility parameter (α value)	

B. Customer's Schedulable Loads

In the SGRA simulation, 5,555 customers with a total of 208,000 loads are considered. The load of each customer is classified into two categories: non-schedulable and schedulable loads. Non-schedulable loads cannot be arbitrarily rescheduled and are fixed in time. A set of 18 types of schedulable loads is potentially available for rescheduling as indicated by each customer using an α-model based on the coefficient of variation method [9]. Using probabilistically generated profiles for the 18 schedulable loads for each customer, a total of 56,642 schedulable assets at 5,555 customer locations were randomly generated using the data from Table III for each day [9]. The penetration levels show the probability that each appliance is present at a customer location. For each appliance, the mean power and the originally intended start time (i.e., before DR) is also probabilistically generated. Table II indicates an availability window and a flexibility parameter (i.e., the α value) associated with schedulable appliance. The availability window indicates that the appliance can be shifted forward

or backward within the window. The flexibility parameter or shift factor is specified as the threshold metric to determine the participation of the customer. For example, if the flexibility parameter is 0.85, it indicates that the CIP must be at least 15% lower than the RTP for that appliance to be made available by a customer for DR by the aggregator.

C. Pricing Data

The day-ahead forecast pricing information from the utility and spot market used in the simulation is obtained from ComEd residential RTP and PJM, respectively [15], [16].

TABLE III
SCHEDULABLE SMART APPLIANCES

penetration (%)	mean power (kW)	power std. dev. (kW)	duration (15-minute interval)	start mean (hour)	start std. dev. (hour)
70	0.5	0.05	4	7	1
70	0.5	0.05	4	14	3
70	0.5	0.05	4	17	1
50	0.75	0.1	3	7	1
50	0.75	0.1	3	14	3
50	0.75	0.1	3	17	1
30	1	0.2	2	7	1
30	1	0.2	2	14	3
30	1	0.2	2	17	1
100	0.25	0.01	8	7	1
100	0.25	0.01	8	14	3
100	0.25	0.01	8	17	1
10	1.5	0.3	2	7	1
10	1.5	0.3	2	14	3
10	1.5	0.3	2	17	1
80	0.4	0.05	6	7	1
80	0.4	0.05	6	14	3
80	0.4	0.05	6	17	1

D. Aggregator

The aggregator is a market entity that interfaces the residential end user with the spot market (i.e., bulk electricity market). The aggregator is envisioned as either an independent firm in a contract with the energy delivering entity (i.e., distribution utility) for the use of the electricity distribution assets (e.g., feeders, protection switchgear), or a separate unit within the energy delivering entity for managing a new DR program such as the SGRA.

By presenting the customers with the choice of day-ahead CIP (offered by the aggregator) and the day-ahead RTP (offered by the utility company), the SGRA model provides the customers with an option to trade their comfort level for a lower electricity bill via load rescheduling. For brevity and a focused scope, the (a) customer-utility and (b) aggregator-utility interactions are not considered in this study.

The scheduling problem is proposed as a day-ahead AP maximization problem using a 15-minute time interval. The AP term (P) comprises the following components: (a) the revenue from the customers willing to reschedule loads and paying the CIP (S); (b) the payment collected from the bulk electricity market for selling a negative load including during peak hours (N); and (c) the expense for buying electricity from the bulk electricity market for supplying the rescheduled customer loads (B). Detailed mathematical definitions of the above-mentioned terms occur in [9]. The objective function for the optimization of the SGRA problem is formulated in (1).

$$P = N + S - B \tag{1}$$

III. Machine Learning

A. Data Evaluation

The data for this study was generated by simulating the SGRA problem over a time horizon of 365 days on the HPC (Summit) environment [2]. The application of HPC reduces the computation time for this data-intensive resource allocation problem [17].

The primary dataset is divided into two sub-datasets for developing ML methods for relating AP to information on customer loads (Model 1), and the other for relating AP to information on forecast electricity prices (Model 2). The first and second sub-datasets contains information on 5,555 schedulable loads and 365 observations of daily electricity price (at 15-minute intervals) for the aggregator, respectively. Each dataset is divided randomly into a training dataset (75%) and a testing dataset (25%). Table IV summarizes the definition of the two sub-datasets and their respective parameters.

TABLE IV
MACHINE LEARNING DATASETS

parameters	Model 1	Model 2
dataset size	5,555	365
input feature vector	schedulable loads	electricity prices
number of elements	18	96
element type	binary	numerical
output (response)	AP from one customer	AP from one day
training: testing (% of available data)	75:25	75:25

1) Model 1: This model is designed to investigate the effect of schedulable loads at a randomly chosen customer location on the AP. By randomly selecting a day from the year under consideration, we are presented with data corresponding to 56,498 schedulable loads probabilistically generated from Table II. The dataset is sorted in descending order of AP, and three classes (high, medium, and low) of equal number of customers are demarcated. The feature vector of this model contains 18 elements representing the availability of 18 types of schedulable loads. Any one customer may not have all the 18 schedulable loads. The availability of a schedulable load in a customers house is treated as a binary variable1, if available or 0, if not available.

2) Model 2: This model is intended to study the influence of the forecast of day-ahead electricity prices on the daily AP. This dataset is also arranged in descending order of AP and

divided equally into two categories (high and low). To match the scheduling window of the aggregator, the feature vector of this model contains 96 elements, representing the day-ahead forecast price (in cents/kWh) in 15-minute intervals for the 24-hour period. Each element is a rational numerical quantity.

B. Model Creation and Validation

While the data for the ML was obtained from the Summit HPC server (detailed in Section II), the ML algorithms were executed on a desktop computer with an Intel core i5-4200U 2.30 GHZ CPU, 4 GB of RAM, and Microsoft Windows 10 Home operating system. The ML toolbox of MATLAB (version 2018a) was employed for applying various ML algorithms due to its ease and user-friendly GUI environment.

Classification and regression models were designed to compare the performance of ML with the SGRA simulation results. The ML classifiers of MATLAB can perform training to search for the best classification model type, including decision trees, discriminant analysis, k-Nearest Neighbors (KNN), support vector machine (SVM), and ensemble methods [18]. The ML regression model options include regression tree, SVM, Gaussian process regression (GPR), and ensemble of trees [19]. For both classification and regression, the algorithms that gave consistent performance and high accuracy were selected for testing.

To avoid the over-fitting problem in ML, a k-fold cross-validation was conducted to verify that each model is not over-fitted. In this study, the training dataset is randomly partitioned into five mutually exclusive subsets (roughly equal size) and one is reserved for validation while others are used for training. This process is repeated k times such that each subset is used exactly once for validation [20].

C. Model Evaluation

To evaluate the ML model performance, it is necessary to identify appropriate performance metrics. The prediction accuracy, ACC, shown in (2), is used to evaluate the performance of ML classifiers. The root-mean-square error (RMSE) and the normalized root-mean-square error (NRMSE) are shown in (3) and (4), respectively. The latter is used to measure the differences between observed values and predicted values. The variables $X_{pred,corr}$ and X_{pred},total are the correct and total predictions, respectively; X_{obs} is the observed data, which is a form of the testing dataset; M is the testing sample size; and $X_{obs,max}$ and $X_{obs,min}$ are maximum and minimum observations, respectively.

$$ACC = \frac{X_{pred,corr}}{X_{pred,total}} \tag{2}$$

$$RMSE = \sqrt{\sum \frac{(X_{pred} - X_{obs})^2}{M}} \tag{3}$$

$$NRMSE = \frac{RMSE}{X_{obs,max} - X_{obs,min}} \tag{4}$$

IV. Results

A. Overview

The algorithm giving the highest ACC or lowest NRMSE varies, depending on the randomly selected training dataset and randomly divided subsets during ML validation (detailed in Section III). KNN and GPR show high accuracy for the classification and regression models, respectively and are applied to all the testing data, for consistency purposes.

In addition to the prediction accuracy, a confusion matrix is used to examine if all classes are being predicted equally well by the model. Besides the NRMSE value, predicted values versus the observed values are plotted, as shown in Figs. 1-4.

B. Evaluation of Customer Schedulable Loads

The classification system is trained to distinguish the testing data among high, medium, and low. As shown in Table V, the overall accuracy of Model 1 is 57.27%. The confusion matrix contrasting the model-predicted label against the total observed label (as percentages) is shown in Table VI. The model identifies the high and low classes of AP with accuracies of 66.3% and 61.1%, respectively. All correct predictions are located on the main diagonal of Table VI, and the off-diagonal elements represent the misidentifications by the classifier. The model underperforms when classifying the medium category; however, this is not unexpected because the AP from each customer is not uniformly distributed and the threshold of the medium category is set to be narrow to make sure each class has an equal number of observations.

The scatter plot shown in Fig. 1 suggests a rather strong correlation between the predictions by Model 1 and the true responses (i.e., observed values). Note that, in Fig. 1, each dot represents the aggregator profit corresponding to one of the 5555 customers. However, a few points that are vertically distant from the main diagonal line indicate possible outliers

TABLE V
EVALUATION RESULTS

parameters	Model 1: scheduable loads	Model 2:pricing data		
		RTP-forecast	spot-forecast	RTP-forecast + spot-forecast
classification ACC	57.27%	85.56%	84.44%	80.00%
regression NRMSE	9.34%	10.13%	12.20%	9.55 %

TABLE VI
CONFUSION MATRIX OF MODEL 1

		actual class		
		high	medium	low
predicted class	high	66.34%	29.96%	10.96%
	medium	26.49%	46.63%	27.96%
	low	7.18%	23.41%	61.07 %

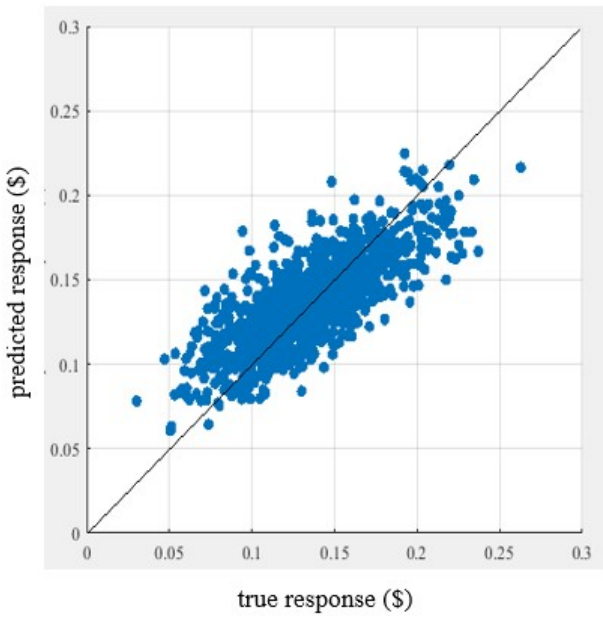

Fig. 1. True values versus predicted values for Model 1. Each dot represents the aggregator profit corresponding to one of the 5555 customers.

when the true response is either relatively small or large. The correlation possibly shows that by knowing the set of available schedulable loads, Model 1 can predict the impact of those loads on the AP, thus enabling the aggregator to accept only the impactful loads for rescheduling.

C. Evaluation of Pricing Data

The day-ahead forecast prices from the utility and the spot market, and the combination of those two prices are used in Model 2 as input predictors. The ideal predictor in the classification models is different than in the regression models. Table V illustrates the performance of Model 2 with three types of electricity prices as input predictors. The highest classification ACC with 85.56% is found by considering the forecast real-time price from the utility only. When combining the two prices in a hybrid mode, the lowest NRMSE value (9.55%) can be achieved, even with the worst classification ACC (80.00%). The ML model may not be able to distinguish the classes of the data but can still give a predicted value that is close to the true response.

As shown in Table VII, the confusion matrix demonstrates the misclassification similarity between the two classes for all three predictors. The testing dataset of Model 2 includes a sample of 90 days from the 365 days data available. In Figs. 2 - 4, scatterplots of the predicted values versus the observed values show similar patterns for all three predictors. The scatterplots show that the models have two subsections of performance. When the true response (observed AP) is between $400 and $900, there is a strong correlation between the predictions by Model 2 and the true responses. When the

TABLE VII
CONFUSION MATRIX OF MODEL 2

predictor	predicted class	actual class: high	actual class: low
RTP-forecast	high	40	8
	low	5	37
spot-forecast	high	38	7
	low	7	38
RTP-forecast + spot-forecast (hybrid price)	high	37	10
	low	8	35

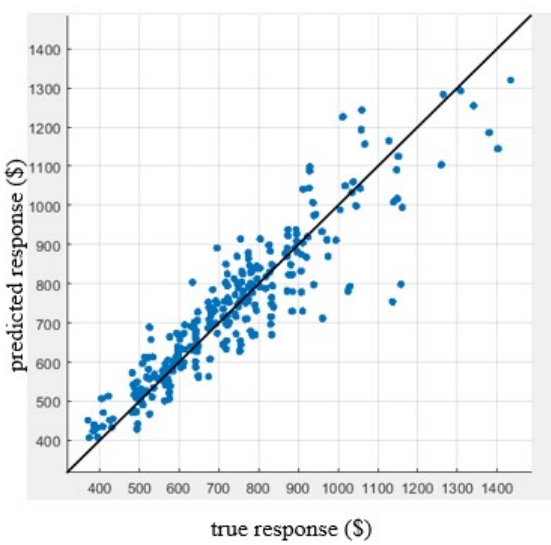

Fig. 2. True values versus the predicted values for Model 2 with RTP-forecast as predictor. Each dot represents the aggegrator profit of one day in the sample year under study.

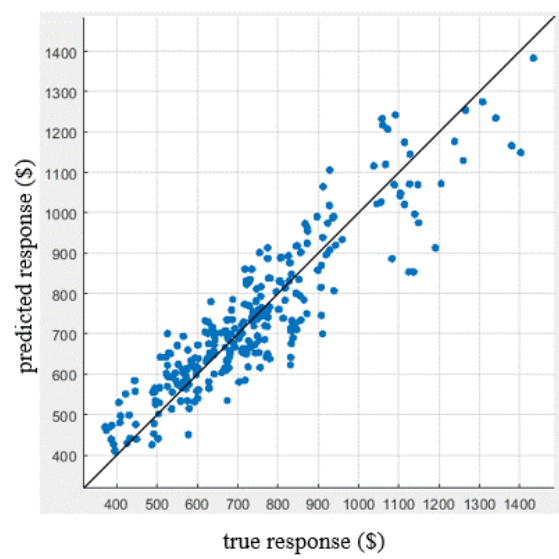

Fig. 3. True values versus the predicted values for Model 2 with spot-forecast as predictor. Each dot represents the aggegrator profit of one day in the sample year under study.

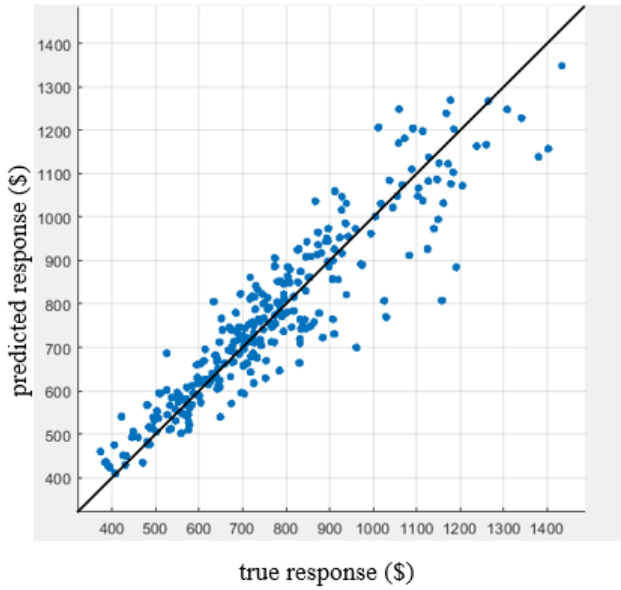

Fig. 4. True values versus the predicted values for Model 2 with spot-forecast as predictor. Each dot represents the aggegrator profit of one day in the sample year under study.

observed AP is more than $900, Model 2 is more likely to either underestimate or overestimate the actual values.

V. Conclusion

In this paper, we applied supervised machine learning methods for determining the impact of a set of schedulable loads and the day-ahead forecast of electricity prices on predicting aggregator profit. The results show that the classifier can objectively identify the set of schedulable loads that may yield high aggregator profit. The high prediction accuracy of Model 2 indicates that the day-ahead electricity prices from the utility and the spot market have a significant impact on aggregator profit. The classification results can serve as an indicator for the minimum set of schedulable loads needed to obtain a desired level of profits by an aggregator. This will potentially help both the customer and the aggregator to identify loads that make significant impact on the SGRA demand response program. Such an effort in identification of impactful loads is expected to increase willingness among customers to participate in a demand response program and reduce computational burden for aggregators. The regression model is expected to increase awareness of day-ahead aggregator profit, and the NRMSE value can be used to assess the performance of the chosen machine learning method. The data from the year-long simulation of the SGRA problem used in the machine learning methods here are given in [21].

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