A Novel Demand Response Model and Method for Peak Reduction in Smart Grids – PowerTAC

Extended Abstract

Sanjay Chandlekar
International Institute of Information Technology
Hyderabad, India
sanjay.chandlekar@research.iiit.ac.in

Arthik Boroju
Indian Institute of Technology Ropar, India
arthikvishwakarma@gmail.com

Shweta Jain
Indian Institute of Technology Ropar, India
shwetajain@iitrpr.ac.in

Sujit Gujar
International Institute of Information Technology
Hyderabad, India
sujit.gujar@iiit.ac.in

ABSTRACT

We study the Demand Response behavior of smart grid customers in response to the offered discounts for peak reduction. We propose a model that depicts the probability of a customer reducing its load as a function of the discounts offered. This function is parametrized by the rate of reduction (RR). We provide an optimal algorithm, MJS–ExpResponse, that allocates the discounts to each customer by maximizing the expected reduction under a budget constraint. When RRs are unknown, we propose a Multi-Armed Bandit based online algorithm, namely MJSUCB–ExpResponse, to learn RRs. We experimentally show that it exhibits sublinear regret and showcase its efficacy in a real-world smart grid system using the PowerTAC simulator as a test bed.

KEYWORDS

Demand Response in Smart Grids; Peak Reduction; PowerTAC

ACM Reference Format:
Sanjay Chandlekar, Arthik Boroju, Shweta Jain, and Sujit Gujar. 2023. A Novel Demand Response Model and Method for Peak Reduction in Smart Grids – PowerTAC: Extended Abstract. In *Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), London, United Kingdom, May 29 – June 2, 2023*, IFAAMAS, 3 pages.

1 INTRODUCTION

Demand Response (DR) involves distribution companies (DC) offering the agents monetary incentives to voluntarily optimize their electricity load in *Smart grid*. There are many approaches, such as auction-based mechanisms [7, 8] and dynamic pricing [2] to achieve DR. The major challenge with these approaches is that different agents may respond differently to the given incentives. Thus, to increase agent participation, it becomes crucial to learn their reaction toward these incentives. Learning agents' behavior is challenging due to the uncertainty and randomness that creeps in due to exogenous factors like weather [5, 6]. Works like [5, 6] consider a very simplistic model – when DC offers to an agent incentive more than what it values, the agent reduces every unit of electricity it consumes with a certain probability independent of the incentive. This probability is termed as reduction probability (RP) [3, 6]. RPs are learned using multi-armed bandit (MAB) solutions. There are three primary issues with these approaches. (i) Agents' valuations need to be elicited [3, 6], which adds additional communication complexity, (ii) agents reduce all with RP else nothing, and (iii) RPs do not change with incentives. In the real world, increasing incentives should lead to an increase in RP. Our work considers the model where the RP is a function of incentives offered and not a constant for an agent, and reduction is not binary.

We need to conduct experiments with smart grids to model RP as a function of incentive. However, any DR technique (or such experiments) proposed for a smart grid should also maintain the grid's stability. The only way to validate that the proposed technique would not disrupt the grid operations while achieving DR is to test it on real-world smart grids, which is practically impossible. Nevertheless, Power Trading Agent Competition (PowerTAC) [4] provides an efficient and very close-to real-world smart grid simulator intending to facilitate smart grid research. We first perform experiments with PowerTAC to observe the behavior of different agents for the offered incentives. With rigorous experiments, we propose our model ExpResponse. We observe that the agents respond quickly to the incentives; however, more incentives may not substantially increase reduction guarantees. Different agents may have a different rate of reduction (RR) to incentives that determine how fast RP changes w.r.t. incentives. It also models the consumer valuation for one unit of electricity.

We propose an optimization problem for the DC to maximize the expected peak reduction within the given budget. We then provide an optimal algorithm, namely MJS–ExpResponse, for the case when the reduction rate (RR)s of the agents are known. When RRs are unknown, we employ a standard MAB-algorithm, MJSUCB–ExpResponse, to learn RRs. Our experiments with synthetic data exhibit sub-linear regret (the difference between the expected reduction with known RRs and the actual reduction with MJSUCB–ExpResponse). With this success, we adopt it for PowerTAC set-up and experimentally show that it helps in reducing peak demands substantially and outperforms baselines such as distributing budget equally across all agent segments. It achieves close to 14% reduction in peak demands and more than 9% reduction in peak demand penalties compared to when no discount was offered.

Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), A. Ricci, W. Yeoh, N. Agmon, B. An (eds.), May 29 – June 2, 2023, London, United Kingdom.

Algorithm 1: MJS–ExpResponse Algorithm

Input: Budget b, n, RR vector λ
Output: Final Allocation vector c

$cost \leftarrow 0, c \leftarrow 0_n$; // initialization
while $cost \leq b$ **do**
  $d \leftarrow 1, l \leftarrow 1$
  while $d \leq n$ **do**
    $\Delta_d^{c_d+1} \leftarrow (1 - e^{-\lambda_d(c_d+1)}) - (1 - e^{-\lambda_d c_d})$
    $\Delta_l^{c_l+1} \leftarrow (1 - e^{-\lambda_l(c_l+1)}) - (1 - e^{-\lambda_l c_l})$
    if $\Delta_d^{c_d+1} > \Delta_l^{c_l+1}$ **then**
      $l = d$
    $d = d + 1$
  $c_l = c_l + 1$ and $cost = cost + 1$
return c // final allocation

2 MATHEMATICAL MODEL

We consider $N = \{1, 2, \ldots, n\}$ agents available to prepare for DR at any given timeslot. A DR model can further incentivize agents, offering c_i to agent i, to shift their usages from peak to non-peak timeslot, which agents may do stochastically. For each agent i, this stochasticity can be modeled by associating the probability of reducing demand in the desired timeslot i. We call this probability as *reduction probability* (RP) $p_i(c_i)$. Based on the PowerTAC experiments, we conclude that the reduction probability function can be modeled by an exponential probability function, i.e., $p_i(c_i) = 1 - e^{-\lambda_i c_i}, \forall i \in N$. We call λ_i as its reduction rate (RR).

ExpResponse-The Optimization Problem: The budgeted demand response problem is given as:

$$\textbf{max}_{c_i} \sum_{i=1}^{n} (1 - e^{-\lambda_i c_i}) \ s.t. \sum_{i=1}^{n} c_i \leq b \quad (1)$$

We next present an optimal algorithm MJS–ExpResponse to efficiently solve Equation 1 when (Algorithm 1) RR (λ) values are known. When RRs are unknown, we provide MJSUCB–ExpResponse algorithm that estimates it (Algorithm 2), which is motivated by multi-armed bandit literature [3, 6] and uses the linear search over the possible range of values of RR. We have the following results:

Theorem 2.1. *MJS–ExpResponse is optimal.*

MJSUCB–ExpResponse proposes a way for estimating RR of each agent using the following **LinearSearch() method**. It calculates $\hat{p}_i(c_i) = \frac{SuccHist(i,c_i)}{OfferredHist(i,c_i)}$ for calculating candidate values of RR. We then determine $\hat{\lambda}_i$ that minimizes the squared error loss between the historical probabilities and the current probabilities, i.e., $\hat{\lambda}_i \in argmin_l \sum_{c_i \in [b]} \left(\hat{p}_i(c_i) - (1 - e^{-lc_i})\right)^2$, for each discount value.

3 EXPERIMENTS IN POWERTAC

We need to make slight adjustments in MJSUCB–ExpResponse to use it in PowerTAC, and the details can be found in [1].

Baseline: We consider the baseline of uniformly allocating the budget to all the groups. We also compare the efficacy against the strategy when we do not provide groups with any DR signals.

Algorithm 2: MJSUCB–ExpResponse Algorithm

Input: Budget b, n, Batch Size bS, T
Output: Allocation $\{c_t\}_{t=1}^T$

Initialize $\hat{\lambda}, \hat{\lambda}^+$ randomly // n-dimensional vectors
Initialize $offeredInst, successInst, offeredHist$ and $successHist$ to 0 // 2D matrices of size $n \times b$
$t \leftarrow 0$
while $t < T$ **do**
  $\{c_{t'}\}_{t'=t}^{t+bs} =$ MJS–ExpResponse$(b, n, \hat{\lambda}^+)$
  for $i = 1 \rightarrow n$ **do**
    if $c_t(i) \neq 0$ **then**
      $offeredInst(i, c_t(i))$ += bS
      $successInst(i, c_t(i))$ += # Successes for agent i
  Update $Hist = \{Hist, offeredInst, successInst\}$
  Clear $offeredInst, successInst$
  $t \leftarrow t + bS$
  $[\hat{\lambda}, \hat{\lambda}^+] \leftarrow LinearSearch(Hist, n, b, t)$
return $\{c_t\}_{t=1}^T$

Table 1: Performance Comparison

Criteria	Peak (MWh)		Average Penalty	
Method	$b = 15$	$b = 7.5$	$b = 15$	$b = 7.5$
No Discount	70.2	70.2	249355	249355
Baseline	68.1	67.8	233768	227070
Average Over Last 10 Weeks of Training				
MJSUCB–ExpResponse-W	60.2	64.1	226374	228351
MJSUCB–ExpResponse-UW	60.0	61.4	225775	228276

Evaluation Metrics: We evaluate MJSUCB–ExpResponse's performance on two metrics, (i) peak demand reduction capability and (ii) the reduction in *capacity transaction* penalties. We perform experiments with different initial budgets for a total of 210 simulation weeks in each set by randomly initializing RR values for each group and calculate the budget allocation based on MJS–ExpResponse (for both weighted and unweighted, called MJSUCB–ExpResponse-W and MJSUCB–ExpResponse-UW, respectively). For each customer group, we publish separate ToU tariffs and keep the same tariffs active for 3 simulation days and invoke the MJSUCB–ExpResponse at the end of the 3rd day. Based on the Algorithm 2, we calculate the next set of $\hat{\lambda}^+$ values for each group, calculate the next discount allocation, and publish the new ToU tariffs. We perform 2 sets of experiments with budget $b = 15\%$ and $b = 7.5\%$. Table 1 shows our final results.

4 CONCLUSION

The paper proposed a novel DR model where the customer's behavior depends on the offered incentives. Using the experiments on the PowerTAC real-world smart grid simulator, we first modeled the ExpResponse function, then proposed MJS–ExpResponse for optimal budget allocation with known RR and MJSUCB–ExpResponse that achieves sublinear regret on the simulated data. MJSUCB–ExpResponse further significantly reduces peak demands and capacity transactions just within 200 weeks of simulation on PowerTAC.

REFERENCES

[1] Sanjay Chandlekar, Arthik Boroju, Shweta Jain, and Sujit Gujar. 2023. A Novel Demand Response Model and Method for Peak Reduction in Smart Grids – PowerTAC. https://doi.org/10.48550/ARXIV.2302.12520

[2] Arman Goudarzi, Yanjun Li, Shah Fahad, and Ji Xiang. 2021. A game theory-based interactive demand response for handling dynamic prices in security-constrained electricity markets. *Sustainable Cities and Society* 72 (2021). https://doi.org/10.1016/j.scs.2021.103073

[3] Shweta Jain, Balakrishnan Narayanaswamy, and Y. Narahari. 2014. A Multiarmed Bandit Incentive Mechanism for Crowdsourcing Demand Response in Smart Grids. In *AAAI Conference on Artificial Intelligence*. Canada.

[4] Wolfgang Ketter, John Collins, and Prashant Reddy. 2013. Power TAC: A competitive economic simulation of the smart grid. *Energy Economics* 39 (2013), 262–270. https://doi.org/10.1016/j.eneco.2013.04.015

[5] Yingying Li, Qinran Hu, and Na Li. 2018. Learning and Selecting the Right Customers for Reliability: A Multi-Armed Bandit Approach. In *2018 IEEE Conference on Decision and Control (CDC)*. 4869–4874. https://doi.org/10.1109/CDC.2018.8619481

[6] Jain Shweta and Gujar Sujit. 2020. A multiarmed bandit based incentive mechanism for a subset selection of customers for demand response in smart grids. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 34. 2046–2053.

[7] Ming Zeng, Supeng Leng, Sabita Maharjan, Stein Gjessing, and Jianhua He. 2015. An Incentivized Auction-Based Group-Selling Approach for Demand Response Management in V2G Systems. *IEEE Transactions on Industrial Informatics* 11, 6 (2015), 1554–1563. https://doi.org/10.1109/TII.2015.2482948

[8] Ruiting Zhou, Zongpeng Li, and Chuan Wu. 2015. An online procurement auction for power demand response in storage-assisted smart grids. In *2015 IEEE Conference on Computer Communications (INFOCOM)*. 2641–2649. https://doi.org/10.1109/INFOCOM.2015.7218655