An Example Article*

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Key words. example, LaTeX

AMS subject classifications. 68Q25, 68R10, 68U05

1. Notation and Problem Setup.

We consider the system of n thermostatically controlled loads, indexed by $i = 1, 2, \ldots, n$. We suppose that there is an aggregator A which send matrices $\bar{P}(t)$, $t = 1, \ldots, T$.

We refer $P_i(t) \in \mathbb{R}^{N\times N}$ as a transition matrix of load i, $i = 1, \ldots, n$, and N is a number of possible states of any load (all loads have the same number of states). Each load has its own behaviour defined as a function $P_i(t)$. All these behaviours are independent. We also suppose that any $\bar{P}(t)$ and $P_i(t) \in \mathcal{P} = \{P^{(1)}, P^{(2)}, \ldots, P^{(m)}\}$. Each load is allowed to accept or reject a transition matrix $\bar{P}(t)$ according to the following rule:

$$\bar{P}_i(t) = \begin{cases} \bar{P}(t), & \text{if } \Omega(\bar{P}(t), P_i(t), t) = 1 \\ P_i(t), & \text{otherwise,} \end{cases}$$

where $\Omega(P_1, P_2, t)$ is some decision rule which meets all legal and customer requirements. For the sake of simplicity we may assume this rule is known (i.e. a part of the contract), however, it is not required: we may learn it on-the-fly. Also, as we have only m different matrices, Ω is a time-dependent matrix where $\Omega_{ij}(t) = 1$ if having own matrix $P_k(t) = P^{(i)}$ a load k accepts proposed matrix $\bar{P}^{(j)}$ at time t.

We refer $\pi_i(t)$ as a unit vector corresponding to the state of load i, $1 \le i \le n$, at time t, so that

$$\pi(t) = \frac{1}{n}\sum_{i=1}^{n} \pi_i(t).$$

We also assume the the power consumption q at each state is known, so that the total power consumption $s(t)$ is

$$s(t) = n \cdot \pi(t)^\top q.$$

We refer $\bar{s}(t)$ as the power requested by the system operator at time t.

*Submitted to the editors DATE.

Funding: This work was funded by the Fog Research Institute under contract no. FRI-454.

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We also assume the loss function of the system operator to be

$$\sum_{i=1}^{T} c(t)|\bar{s}(t) - s(t)|,$$

where $c(t) > 0$ is non-negative cost function.

In this research we implement an incentive-based model of users motivation to participate in the curtailment program. In particular we consider the Emergency Demand-Response Program (EDRP) setting here, in which consumers get incentive payments for reducing their power consumption during reliability triggered events (see [2]). Consumers may choose not to curtail and therefore to forgo the payments, which are usually specified beforehand [16]. Due to privacy protection reasons ([9]) the aggregator is forbidden to observe exact loads accepting a curtailment request, but it is important to know the total amount of these loads for two reasons:

1. As the aggregator's budget is strictly limited, it must estimate expenses for incentive payments.
2. Most of the DR incentive-based programs limit the total amount of curtailment hours to avoid user disturbance (typically 200 hours/year [1])

To sum up, the exact objective will be:

$$\min \sum_{i=1}^{T} c(t)|\bar{s}(t) - s(t)| \tag{1.1}$$

$$s.t. \sum_{t=1}^{T} k(t) \leq K \tag{1.2}$$

2. Solution.

In the following section we treat 1.1 as a **linear contextual bandit with knapsack** problem [4]. Define the policy as some mapping from the context $f(t)$ to the matrix number $i \in \{0, 1, \ldots, m\}$ (a.k.a. arm). Define the regret $\mathcal{R}_T^{\nu}$ as the difference between performances under the best policy available and under some policy ν:

$$\mathcal{R}_T^{\nu} = \sum_{t=1}^{T} (r^*(t) - r^{\nu}(t)) \tag{2.1}$$

The goal is to learn the policy ν which minimizes the regret:

$$\begin{aligned} \min_{\nu} \mathcal{R}_T^{\nu} &= \min_{\nu} \sum_{t=1}^{T} (r^{\nu}(t) - r^*(t)) \\ s.t. \sum_{t=1}^{T} k(t) &\leq K \end{aligned} \tag{2.2}$$

where the penalty is defined as

$$r^{\nu}(t) = c(t)|s^{\nu}(t) - \bar{s}(t)|$$

and $k(t)$ is the number of loads who accepted the curtailment request at the time t, K is the contract limit for user disturbance and ν is the policy being used. Hereafter we refer to $r^{\nu}(t)$ as $r(t)$.

In this form of bandits setup we face two major troubles:

1. General bandit with knapsack problem setup [4] consider penalties as a random independent variables over time and arms. Both assumptions here are false: our choices from the past strongly affects the current reward distributions.
2. Variables $k(t)$ are unobservable, hence we can only ensure thresholds with some probability.

To deal with these issues consider the the mechanics of how $s(t)$ depends on aggregator's actions. Suppose that by the time t we have a (possibly unknown) state-distribution $\pi(t)$. It is easy to see that if each device chooses its own matrix, and we denote the number of devices which have chosen matrix P_j as n_j, then the next-moment consumption with no control will be:

$$s(t|0) := \sum_{j=1}^{m} n_j(t) q^T P_j \pi(t) = \sum_{j=1}^{m} n_j(t) f_j(t|0) \tag{2.3}$$

and if we pull i^{th} arm, the consumption will be:

$$s(t|i) := \sum_{j=1}^{m} n_j(t) q^T (\Omega_{ij}(t) P_i + (1 - \Omega_{ij}(t)) P_j) \pi(t) = \sum_{j=1}^{m} n_j(t) f_j(t|i) \tag{2.4}$$

The model appears to be linear over unknown variables $n_j(t)$ and some vector $f(t|i) := \{f_j(t|i)\}_{j=1}^{m}$, $i \in [0, 1, \dots m]$ which we know if we have $\pi(t)$ and $\Omega_{ij}(t)$. Therefore it is surprisingly convenient to consider $f(t|i)$ as a feature vector of an arm i at the moment t. Note, that the features $f_j(i|t)$ have the natural interpretation as the amount of energy being consumed by an average device which has $\bar{P} = P_j$ at the time t if we pull the i-th arm. Moreover, we also have an estimator for budgeted variable: $k(t|i) = \sum_{i=1}^{m} \Omega_{ij} n_j$.

The Bandit. The above mentioned arm feature vectors (a.k.a. arm-contexts) $f(i|t)$ reveals a straightforward "linear contextual bandit with knapsack" setup:

$$\begin{aligned}
&\min_{\nu: t \to \{0,1...m\}} \sum_{t=1}^{T} \mathcal{L}_t \left(n(t)^T f(t|\nu(t)) \right) \\
&s.t. \, \mathbb{E} \sum_{t=1}^{T} k(t|\nu(t)) \leq K \\
&\sum_{j=1}^{m} n_j(t) = n \, \forall t \\
&n_j(t) \geq 0 \, \forall t
\end{aligned}$$

where $n(t) = \{n_j(t)\}_{j=1}^m$ (do not miss it with n – the total amount of devices), and $\mathcal{L}_t(x)$ is a loss function. In this work two classical demand-response loss functions are considered. The first one is a trivial mapping:

$$\mathcal{L}_t(x) = x \tag{2.5}$$

which gives the consumption minimization setup:

$$\begin{aligned}
&\min_{\nu: t \to \{0,1...m\}} \sum_{t=1}^{T} n(t)^T f(t|\nu(t)) = \min_{\nu} \sum_{t=1}^{T} s^{\nu}(t) \\
&s.t. \, \mathbb{E} \sum_{t=1}^{T} k(t|\nu(t)) \leq K \\
&\sum_{j=1}^{m} n_j(t) = n \, \forall t \\
&n_j(t) \geq 0 \, \forall t
\end{aligned} \tag{2.6}$$

and the second one is the absolute deviation from a given series $\bar{s}(t)$:

$$\mathcal{L}_t(x) = |x - \bar{s}(t)| \tag{2.7}$$

which gives the consumption stabilization setup:

$$
\begin{aligned}
&\min_{\nu:t\to\{0,1\dots m\}} \sum_{t=1}^{T} |n(t)^T f(t|\nu(t)) - \bar{s}(t)| = \min_{\nu} \sum_{t=1}^{T} |s^{\nu}(t) - \bar{s}(t)| \\
&s.t.\, \mathbb{E} \sum_{t=1}^{T} k(t|\nu(t)) \le K \\
&\sum_{j=1}^{m} n_j(t) = n \,\forall t \\
&n_j(t) \ge 0 \,\forall t
\end{aligned} \tag{2.8}
$$

It remains to notice that $n(t)$ is a periodic function over time with a period of 24 hours (at least within one season of a year), so we can consider 2.6 and 2.8 as a set of 24 bandits: each one is learning to make a decision at the assigned hour. Note that these problems are in exact form for recently emerged budgeted bandit solvers ([4] and more (add later)), and all the requirements are met: the divergence between predicted and real consumption may appear only regarding to stochatical fluctuations due to the finiteness of the ensemble, hence we have independence of reward as a function of a context through arms and time (*of course we need a proof here*).

The Algorithm with known $\Omega_{ij}(t)$ and without a knapsack:. Consider a simpler setup when $K = \infty$ i.e. we have no knapsack constraints in our problem. Here τ is the number of steps which a device performs each hour. We also assume that we do not know neither an initial state distribution $\pi(0)$ nor $n_j(t)$. In this case 2.1 is how a dummy algorithm may look like (we assume here a 2.7 loss function).

One may notice that in 2.1 the greedy policy was used, and no exploration steps were proposed. In fact, the greedy policy here turns to be optimal: all the reward variances depend only on unknown vector $n(t)$ and when we learn it we decrease reward variances for all arms simultaneously. Hence, in contrast to the following case, no exploration-exploitation balance is required here.

The Algorithm without a knapsack and without $\Omega_{ij}(t)$. Note that it is not crucial for the previous algorithm to know the oracle $\Omega_{ij}(t)$, as we may learn in the same way we learn $n(t)$. Formally, let i be the arm the aggregator pulled at the moment t, then the consumption will be:

$$
\begin{aligned}
s(t|i) =& n(t)^T f(t|i) = \sum_{j=1}^{m} n_j(t) \sum_{\xi=1}^{\tau} q^T(\Omega_{ij}(t) P_i^{\xi} + (1-\Omega_{ij}(t)) P_j^{\xi}) \pi(t) = \\
&= \sum_{j=1}^{m} \Omega_{ij}(t) n_j \sum_{\xi=1}^{\tau} q^T (P_i^{\xi} - P_j^{\xi}) \pi(t) + \underbrace{\sum_{j=1}^{m} n_j \sum_{\xi=1}^{\tau} q^T P_j^{\xi} \pi(t)}_{s(t|0)}
\end{aligned} \tag{2.9}
$$

and we have a discrete regularized regression problem over the vector $\Omega_i(t) \in \{0,1\}^m$ here:

Algorithm 2.1 Non-budgeted TCL-control with oracle

Require: $\mathcal{P}$, n, $\tau, \Omega_{ij}(t)$

$n_i(0) := 1/n \, \forall i$
$\pi_0 := \frac{1}{n} \sum_{i=1}^{m} n_i(0) u_i$, where u_i is a stationary distribution of the matrix P_i
$A(t) = \{\emptyset\} \, \forall t$ where A(t) is an array of all feature vectors through time which we got at the hour t. It will be used as a learning dataset for the t-th regressor.
$S(t) = \{\emptyset\} \, \forall t$ where S(t) is an array of all s(t) through time which we got at the hour t. These are the targets for the t-th regressor.
for $t := 1 \dots T$ **do**
  Generate the arm contexts $\{f_j(t|i)\}_{j=1}^{m}$ for all $i \in \{0, 1 \dots m\}$:
  $f_j(t|i) := \sum_{\xi=1}^{\tau} q^T (\Omega_{ij}(t) P_i^{\xi} + (1 - \Omega_{ij}(t)) P_j^{\xi}) \pi(t) \quad i \in \{1 \dots m\}$
  $f_j(t|0) := \sum_{\xi=1}^{\tau} q^T P_j^{\tau} \pi(t)$
  if $\bar{s}(t) == 0$ **then**
    Set $i := 0$ (no control) and send it to the ensemble
  else
    $i := \arg\max_{i \in \{1 \dots m\}} \mathcal{L}_t(s(t|i)) := \arg\max_{i \in \{1 \dots m\}} \mathcal{L}_t(n(t)^T f(t|i))$.
    Send the chosen arm i to the ensemble
  end if
  Wait and receive $s(t|i)$ – the actual ensemble consumption
  $A(t)$.append$(f(t|i))$
  $S(t)$.append$(s(t|i))$
  Solve a constrained regression problem to learn real $n_j(t)$:
  $n(t) = \arg\min_{n \in R_+^n} \|A(t)n(t) - S(t)\|^2$, $s.t. \sum_{j=1}^{m} n_j(t) = n$, $n_j(t) \geq 0$, start from $n(t)$
  Calculate next π:
  $\pi(t+1) = \frac{1}{n} \sum_{j=1}^{m} n_j(t) (\Omega_{ij}(t) P_i^{\tau} + (1 - \Omega_{ij}(t)) P_j^{\tau})) \pi(t)$
  if $n_j(t+1)$ are undefined yet **then**
    $n_j(t+1) = n_j(t)$
  end if
end for

$$\underbrace{s(t|i) - s(t|0)}_{target} = \sum_{j=1}^{m} \underbrace{\Omega_{ij}(t)}_{variables} \underbrace{n_j(t) \sum_{\xi=1}^{\tau} q^T (P_i^{\xi} - P_j^{\xi}) \pi(t)}_{features} \tag{2.10}$$

If we also have observations from i-th arm at t-th hour from the past (i.e. this is not the first time we pull this arm at this hour), then we may solve the least-squared optimization problem over $\Omega_{ij}(t)|_{j=j} \in \{0, 1\}^m$ which might reduce the fluctuations of Ω.

The algorithm 2.2 for this case is the essentially the same: the new parts are marked with red.

The Algorithm with a knapsack and without $\Omega_{ij}(t)$. This one is our final result. Note that we just need to apply not a regular UCB1 bandit inside the abovementioned algorithm, but

Algorithm 2.2 Non-budgeted TCL-control without oracle

Require: $\mathcal{P}$, n, τ, $\cancel{\Omega_{ij}(t)}$

$n_i(0) := 1/n \, \forall i$

$\pi_0 := \frac{1}{n} \sum_{i=1}^{m} n_i(0) u_i$

$A(t) = \{\emptyset\} \, \forall t$

$S(t) = \{\emptyset\} \, \forall t$

$\Omega_{ij}(0) = \{0,1\}^{m \times m}$ – random matrix

for $t := 1 \ldots T$ **do**

  Generate arm contexts $\{f_j(t|i)\}_{j=1}^{m}$ for all $i \in \{0, 1 \ldots m\}$:

  $f_j(t|i) := \sum_{\xi=1}^{\tau} q^T (\Omega_{ij}(t) P_i^{\xi} + (1 - \Omega_{ij}(t)) P_j^{\xi}) \pi(t) \quad i \in \{1 \ldots m\}$

  $f_j(t|0) := \sum_{\xi=1}^{\tau} q^T P_j^{\tau} \pi(t)$

  if $\bar{s}(t) == 0$ **then**

    Set $i := 0$ (no control) and send it to the ensemble

    Wait and receive $s(t|0)$ – the actual ensemble consumption

    When we have no control signal, we learn $n_j(t)$

    $A(t)$.append$(f(t|0))$

    $S(t)$.append$(s(t|0))$

    Solve a constrained regression problem to learn real $n_j(t)$:

    $n(t) = \arg\min_{n \in R_+^n} \|A(t) n(t) - S(t)\|^2$, $s.t. \sum_{j=1}^{m} n_j(t) = n$, $n_j(t) \geq 0$, start from $n(t)$

    Calculate next π:

    $\pi(t+1) = \sum_{j=1}^{m} n_j(t) P_j^{\tau} \pi(t)$

  else

    Calculate $s(t|i) = n(t)^T f(t|i)$ for all $i \in \{0, 1, \ldots m\}$

    Calculate variance estimations $\Delta s(t|i)$

    $i := \arg\min_{j \in \{0,1,\ldots m\}} \mathcal{L}_t(s(t|j) + B\sqrt{\Delta s(t|i)})$

    Send the chosen arm i to the ensemble

    Wait and receive $s(t|i)$ – the actual ensemble consumption

    Learn the vector $\Omega_i(t)$ solving optimization problem:

    $$\Omega_i(t) := \arg\min_{\omega \in \{0,1\}^m} \left(\underbrace{(s(t|i) - s(t|0))}_{s} - \sum_{j=1}^{m} \omega_j \, n_j(t) \underbrace{\sum_{\xi=1}^{\tau} q^T (P_i^{\xi} - P_j^{\xi}) \pi(t)}_{g_j} \right)^2 =$$

    $$= \arg\min_{\omega \in \{0,1\}^m} \left(s - w^T g\right)^2$$

    I suppose we need some kind of smooth relaxation here

    Calculate next π:

    $\pi(t+1) = \frac{1}{n} \sum_{j=1}^{m} n_j(t) (\Omega_{ij}(t) P_i^{\tau} + (1 - \Omega_{ij}(t)) P_j^{\tau})) \pi(t)$

  end if

  if $n(t+1)$ is undefined yet **then**

    $n(t+1) = n(t)$

  end if

  if $\Omega_{ij}(t+1)$ is undefined yet **then**

    $\Omega_{ij}(t+1) = \Omega_{ij}(t)$

  end if

end for

the ”bandit-with-knapsack” solver from [4] or something similar.

3. Demand-Response Overview. Smart Grids drew a lot of attention in the recent years. Traditionally, the term ”grid” denotes an electricity system, that supports electricity generation, transmission, distribution and control. Most of them use for direct energy delivery from several large generators to consumers. In contrast, a Smart Grid is an electricity grid which utilise two-way flows of energy and information to establish automated and distributed next-generation energy delivery network [6]. These intelligent technologies are incorporated across the entire system which improve its efficiency, safety and reliability [7].

One of the distinguishing features of such type of networks is demand manageability. This concept of the Demand-Side Management (DSM) includes all activities aiming to alter the consumer’s demand profile to make it match the supply and to effectively incorporate renewable energy sources [3]. Nowadays the major activity in DSM is Demand-Response (DR), which is considered as a subset of the broader category of DSM, together with energy efficiency and conservation programs [12]. According to the United States Department of energy, Demand-Response is ”a tariff or program established to motivate changes in electric use by end-use customers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized” [5]. According to [16], the main objectives of the application of DR scheme may be summarised as:

- Reduction of the total energy consumption both on demand and transmission sides.
- Reduction of the total needed power generation in order to eliminate the need of activating expensive-to-run power plants to meet peak demands. Such overall consumption curtailment may help governments and energy providers to meet their pollution obligations [5, 14, 15].
- Efficient incorporation of renewable energy sources through making the demand follow the available supply fluctuations. Such incorporation may significantly increase the overall system’s reliability in regions with high penetration of wind farms and solar panels [13].
- Reduction or even elimination of overloads in distribution systems.

As shown in figure the principal DR-scheme consists of cooperation of four main participants: a) an Aggregator, b) a System Operator (SO), c) Power Generation Unit(s) d) and Power Consumer(s) [10]. Their interaction is a cyclic process typically started by the SO, which determines the preferred power consumption and sends it to the Aggregator. Next the Aggregator chooses participating loads from available, calculates possible change in demand and sends it back to the SO. And finally the Operator informs the most available substations about the upcoming demand. In such scheme the Aggregator provides the grid’s intelligence executing optimisation procedures pr revealing problems in distribution system [16].

insert scheme

DR Schemes distinct in control architecture they utilise, and in motivation to participate which they provide to customers.

DR Schemes by its architecture. DR schemes may be classified into centralised and distributed programs [18], according to where the decision for the execution program are made. In centralised schemes load activations are managed only by the central utility. Such schemes are easy to implement, but turn to be hard-headed in large and complex systems. However

Example

it remains an effective approach for controlling ensembles of termostatically controlled loads [8], charging systems for electro vehicles [17] and commercial consumers [11]. For example

DR Schemes by its motivation. The proposed motivation schemes usually adopt either price-based or incentive-based approach.

4. Todos.

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