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Detection of Defaulting Participants With Time-Varying Failure Rates in Demand Response ⋆

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Abstract:
In contract-based demand response, there is a possibility that some participants may default on providing their scheduled negawatt energy. Therefore, one of the essential functions of the aggregator is to detect defaulting participants. This paper aims at solving the problem of detecting defaulting participants with time-varying failure rates in contract-based demand response, provided that the aggregator can inspect the total negawatt energy and the individual negawatt energy of a limited number of participants via smart meters. By assuming that there are only a few defaulting participants and they default in all periods, we propose a detection algorithm based on *block-sparse reconstruction*. The proposed algorithm is demonstrated through numerical simulation.

Keywords: demand response, default detection, block-sparse reconstruction.

1. INTRODUCTION

One of the basic requirements of electric power grids is supply-demand balancing. It is not an easy requirement since both supply and demand may change unexpectedly due to various reasons, such as generation unit forced outages, transmission and distribution line outages, and sudden load changes. The power demand and supply disequilibrium can degrade energy quality and even lead to large-scale outages. Traditional power grids face the challenges of increased demand, grid stability and environmental pollution (P. Siano (2014)). The smart grid is envisioned as a new type of power grid that combines smart meters, which are used to measure the power consumption of users with the demand response (DR), which promises solutions for future power grids (E. Heylen et al. (2020), R.E. Geneidy et al. (2020), and M. Barbero et al. (2020)).

DR is defined as (Q Qdr (2006)) "changes in electric usage by customers from their normal consumption patterns to better match the demand for power with the supply." In general, DR programs can be classified into two main categories (M.H. Albadi et al. (2007)): Incentive-Based Programs (IBP) and Price-Based Programs (PBP). Our research is based on IBP, whose process is as follows (L. Gkatzikis et al. (2013)). The aggregator contracts with the customers in advance, and the participants can receive upfront incentive payments or rate discounts. During the contract period, the participants provide the scheduled amount of negawatt energy to the aggregator, for example, by postponing some tasks that require large amounts of power or switching their consumption to alternate power supplies such as batteries. Here, the negawatt energy represents the energy that saved through energy conservation. In this process, the aggregator meters the total amount of negawatt energy in real-time to manage the DR.

However, there will inevitably be some defaulting participants due to demand-side fluctuations. One of the most critical functions of the aggregator is to detect the failure sources quickly and carry out the appropriate procedures. In theory, the detection of defaulting participants in DR can be easily achieved by accessing all participants' smart meters. However, such detection will increase communication costs. Furthermore, it will decrease the social acceptance of DR, because the smart meters have detailed information about how much electricity is used at each time slot, from which one can infer the behavioral patterns of the occupants. Therefore, it is preferable to detect defaulting participants by using more limited information.

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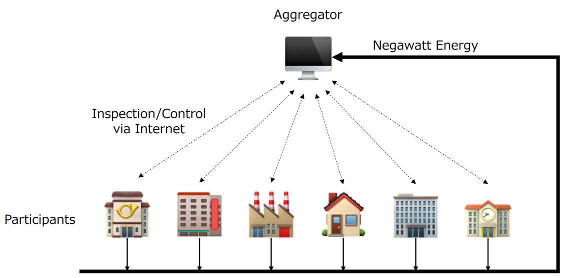


Fig. 1. Demand response

S. Azuma et al. (2020) recently established a framework for detecting defaulting participants by focusing on the fact that the number of defaulting participants is very small, i.e., the distribution of defaulting participants is sparse. This method is based on sparse reconstruction and iterative metering, and as a result, it can detect defaulting participants with little computation and inspection. However, it is assumed that the rate of default with regard to the scheduled negawatt energy is *constant* for each participant. It is somewhat unrealistic since the absolute amount of default might be constant, while in this case, the rate of default will be time-varying.

In this paper, we propose a detection method for defaulting participants with *time-varying* failure rates in DR. Here, we focus on the property that if a participant is defaulting, then the participant is defaulting in all time slots. This assumption is reasonable when the default occurs due to an instrument fault (H.G. Kwag et al. (2014)). Thus, we formulate the detection problem as a "block-sparse" reconstruction problem, and propose a method based on the block-sparse reconstruction algorithm. This method enables us to detect defaulting participants with a small number of inspections exactly. The effectiveness of the proposed method is demonstrated through numerical examples.

2. DEFAULT DETECTION PROBLEM

2.1 Contract-Based Demand Response

We consider a contract-based DR program as shown in Fig. 1, and assume that the contract between the aggregator and each participant is made as follows (S. Azuma et al. (2020)):

(1) The participant pledges a certain amount of negawatt energy to the aggregator at each time slot.
(2) The participants agree to release their smart meter data, but the aggregator can access the data only when an anomaly is detected.
(3) A violation of the scheduled negawatt energy will result in a penalty.

There are some supplementary explanations for the above three clauses. About the first clause, the participant needs to furnish the scheduled amount of negawatt energy to the aggregator at each time slot, as exemplified in Table 1. The second clause is related to data release and is a standard clause in DR contracts, which enhances consumer acceptance. In addition, it reduces the communication costs of the aggregator. The third clause is imposed for minimizing the number of defaulting participants.

Table 1. Example of the scheduled negawatt energy of a participant

Time slot	1	2	...	24
Negawatt energy (kWh)	0.417	0.327	...	0.275

2.2 Problem Formulation

In practice, some participants may default on providing the scheduled negawatt energy. If defaults occur, the aggregator must detect the defaulting participants as soon as possible and change their electricity usage to eliminate the risk of significant failures. Therefore, we consider the default detection problem, which is formulated as follows.

Assume that participants $1, 2, ..., n$ are selected to provide the scheduled negawatt energy at time slots $1, 2, ..., m$. The scheduled negawatt energy (kWh) of participant i at time slot j is denoted as $c_{ij} \in (0, \infty)$, and the failure rate of participant i at time slot j is symbolized by $x_{ij} \in [0, 1]$. Note that $x_{ij} > 0$ if participant i defaults, and $x_{ij} = 0$ $(j = 1, 2, ..., m)$ otherwise. We define the total amount of negawatt energy (kWh) generated by the DR at time slot j as $s_j \in \boldsymbol{R}_{0+}$. Thus, it is evident that

$$\sum_{i=1}^{n} c_{ij}(1 - x_{ij}) = s_j \tag{1}$$

holds at time slot j.

Our problem is to estimate x_{ij} $(i = 1, 2, ..., n$ and $j = 1, 2, ..., m)$ from c_{ij} $(i = 1, 2, ..., n$ and $j = 1, 2, ..., m)$, s_j $(j = 1, 2, ..., m)$, and a limited number of direct inspections of the failure rates.

3. DEFAULT DETECTION FOR TIME-INVARIANT FAILURE RATES

In this section, we review the previous result (S. Azuma et al. (2020)) for the case in which the failure rates are time-invariant, i.e., $x_{i1} = x_{i2} = \cdots = x_{im}$ $(i = 1, 2, ..., n)$.

3.1 Sparsity of Failure Rates

By letting $\bar{x}_i := x_{i1}$ $(= x_{i2} = x_{i3} = \cdots = x_{im})$, we can obtain

$$\bar{C}\bar{x} = \bar{C}1_n - s \tag{2}$$

for m time slots from (1), where

$$\bar{C} := \begin{bmatrix} c_{11} & c_{21} & \cdots & c_{n1} \\ c_{12} & c_{22} & \cdots & c_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ c_{1m} & c_{2m} & \cdots & c_{nm} \end{bmatrix} \in [0, \infty)^{m \times n},$$

$\bar{x} := [\bar{x}_1 \ \bar{x}_2 \ \cdots \ \bar{x}_n]^T \in [0, 1]^n$, $s := [s_1 \ s_2 \ \cdots \ s_m]^T \in [0, \infty)^m$, and 1_n is a n-dimensional column vector whose elements are all one. Then, the default detection problem corresponds to solving the linear equation in (2) with respect to $\bar{x}$.

However, in general, $m < n$ holds in DR; therefore, we cannot uniquely determine the solution $\bar{x}$ to (2). In addition, according to the third clause of the contract, we reasonably suppose that only a few defaulting participants exist. Therefore, vector $\bar{x}$ can be assumed to be sparse.

3.2 Default Detection Based on Sparse Reconstruction

With the prior knowledge that $\bar{x}$ is a sparse vector, we consider utilizing the sparse reconstruction to solve the problem formulated in the previous section.

Consider the linear equation

$$A\bar{x} = b, \tag{3}$$

where $\bar{x} \in \boldsymbol{R}^n$ is the unknown sparse vector, $A \in \boldsymbol{R}^{m\times n}$ and $b \in \boldsymbol{R}^m$ are a constant matrix and vector, respectively. If $\bar{x}$ is sparse, it is known that the solution is given by the following optimization problem:

$$\min_{\bar{x}} \|\bar{x}\|_1 \text{ s.t. } A\bar{x} = b, \tag{4}$$

which can be reformulated as a linear programming (S.S. Chen et al. (2006)).

However, when $m \ll n$, even if the sparsity of $\bar{x}$ is assumed, the number of equations contained in (2) is not sufficient to determine the true sparse $\bar{x}$, which results in an incorrect solution. Therefore, S. Azuma et al. (2020) proposed a default detection method that incorporates the inspection of actual negawatt energy into the sparse reconstruction. It iterates through the following two operations:

(1) Estimate the failure rates of all participants by solving the sparse reconstruction problem in (2).
(2) Inspect the actual negawatt energy of the most suspicious participant indicated by the result of step (1), and reflect the inspection result in the sparse reconstruction problem to be solved at the next iteration.

It has been proven that the above method can exactly estimate the time-invariant failure rates.

4. DEFAULT DETECTION FOR TIME-VARYING FAILURE RATES

Although the time-invariant case was successfully solved in the previous research (S. Azuma et al. (2020)), the time-invariant assumption is not practical at all. In fact, failures occur unexpectedly. Therefore, we need a solution for the time-varying case. In this section, we propose a solution based on the block sparsity of the failure rate vector.

4.1 Block Sparsity of Failure Rates

Let $x_i := [x_{i1}\ x_{i2}\ \cdots\ x_{im}]^T \in [0,1]^m$ $(i = 1, 2, ..., n)$ and $x := [x_1^T\ x_2^T \cdots\ x_n^T]^T \in [0,1]^{nm}$. The former represents the sequence of failure rates of participant i, and the latter is the collection of x_i $(i = 1, 2, ..., n)$ called the *failure rate vector*.

To build a linear equation, we constitute a new coefficient matrix

$$C_i := \begin{bmatrix} c_{i1} & & & \\ & c_{i2} & & \\ & & \ddots & \\ & & & c_{im} \end{bmatrix} \in [0,\infty)^{m\times m}$$

and

$$C := [C_1\ C_2\ \cdots\ C_n] \in [0,\infty)^{m\times nm}.$$

From (1), we obtain

$$Cx = C1_{nm} - s, \tag{5}$$

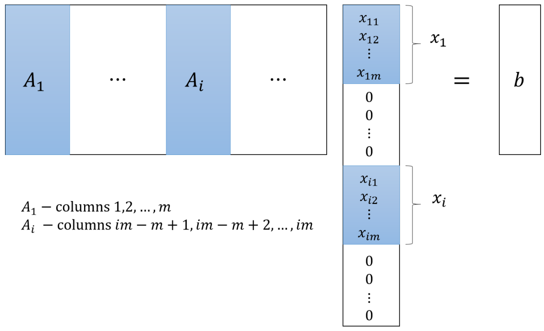


Fig. 2. Image of a block-sparse model

where 1_{nm} is an nm-dimensional column vector whose elements are all one, the matrix C is called the *scheduled negawatt table*, and s is referred to as the *total negawatt vector*.

Equation (5) is similar to (2); however, (5) contains nm unknowns (m times of those of (2)). Therefore, it is not practical to apply the previous method (S. Azuma et al. (2020)) to this case. However, in DR, it is reasonable to assume that

- if participant i defaults, x_{ij} is nonzero for all j,
- if participant i does not default, x_{ij} is zero for all j.

They imply that x has a block-sparse structure. Therefore, we employ a block-sparse reconstruction technique to solve our problem.

4.2 Block-Sparse Reconstruction

In this section, we introduce a framework of block-sparse reconstruction.

Consider the linear equation

$$Ax = b \tag{6}$$

with a block-sparse structure as shown in Fig. 2, where $x \in \boldsymbol{R}^{nm}$ is the unknown block-sparse vector, $A \in \boldsymbol{R}^{m\times nm}$ and $b \in \boldsymbol{R}^m$ are a known constant matrix and vector, respectively. Since $m < nm$, the solution x of the linear equation cannot be uniquely determined. Therefore, M. Stojnic et al. (2009) considered the following convex relaxation for the recovery of a block-sparse vector x:

$$\min_{x} \|x_1\|_2 + \|x_2\|_2 + \cdots + \|x_n\|_2 \text{ s.t. } Ax = b, \tag{7}$$

where $x_i = [x_{i1}\ x_{i2}\ \cdots\ x_{im}]^T \in [0,1]^m$ for $i = 1, 2, ..., n$.

4.3 Default Detection Method

Since $m \ll nm$ for a large n, the exact solution for our problem is not always recovered from the straightforward application of the relaxation of (7). It motivates us to develop an iterative algorithm in a similar way to (S. Azuma et al. (2020)).

In practice, the aggregator can inspect the history of the actual negawatt energy of an arbitrary participant via its smart meter. Based on this idea, the following algorithm is proposed.

(Step 1) Let $BSR(0)$ be the optimization problem in (7) for $A := C$ and $b := C1_{nm} - s$, and set $\boldsymbol{P}(0) := \{1, 2, ..., n\}$, where $\boldsymbol{P}(t)$ is the list of participants whose negawatt energy has never been inspected until t-th iteration.

(Step 2) For each iteration $t = 0, 1, ..., n-1$, implement the following operations:

(1) Solve $BSR(t)$ and obtain a solution $x(t)$, where $BSR(t)$ is the block-sparse reconstruction problem at iteration t.
(2) Set $k(t) \in \boldsymbol{P}(t)$ as the index i of the participant with the largest block of $x(t)$ in the group $\boldsymbol{P}(t)$, which represents the most suspicious participant.
(3) Inspect the history of the negawatt energy of participant $k(t)$ via its smart meter, and get the true failure rate $x^*_{k(t)} \in [0,1]^m$.
(4) Let $BSR(t+1)$ be the optimization problem resulting from the modification of $BSR(t)$. Embed the additional constraint $x_{k(t)} = x^*_{k(t)}$, where $x_{k(t)}$ is the $k(t)$-th block of $x(t)$ with m elements. Set $\boldsymbol{P}(t+1) := \boldsymbol{P}(t) - \{k(t)\}$.

For the above algorithm, the following result is obtained.

Theorem 1. Consider the above algorithm. Assume that C_i $(i = 1, 2, ..., n)$ has positive diagonal entries. If $x_{k(t)} = 0$ in Step 2-(2) for iteration t, then $x(t) = x^*$, where x^* is the true value of the failure rate vector.

This theorem provides the stopping rule for the algorithm and ensures that the algorithm provides the exact solution after a certain number of iterations. It tends to reduce the actual number of inspections, which significantly decreases the amount of data traffic and ensures the efficiency of the aggregator. In addition, it reduces the possibility of inspection for each participant, which protects the private information of most participants.

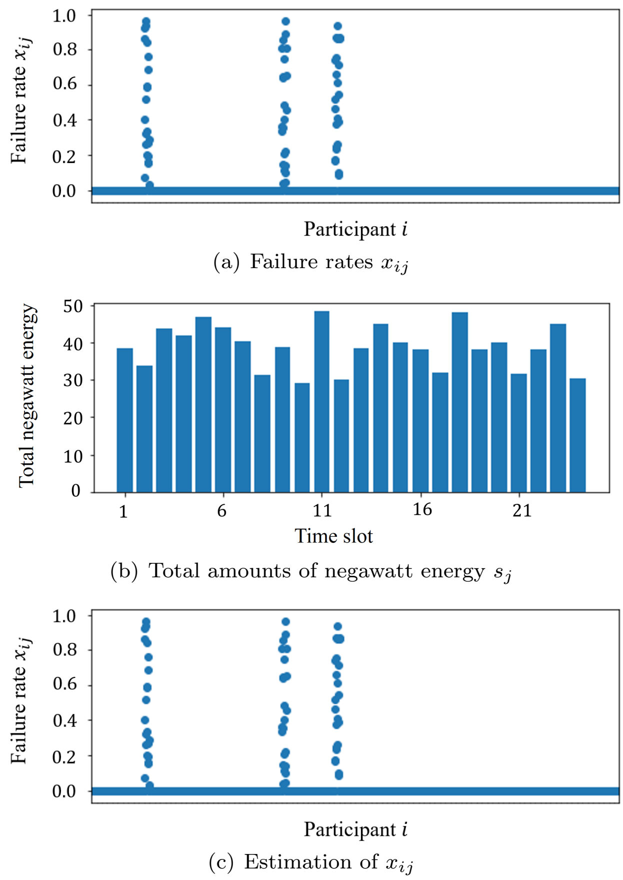
4.4 Numerical Example

In this section, we show how the proposed algorithm efficiently solves the detection problem.

Let us consider the DR with $n = 100$ and $m = 24$. The scheduled negawatt energy c_{ij} $(i = 1, 2, ..., n$ and $j = 1, 2, ..., m)$ is randomly generated from the uniform distribution on the interval $(0, 1]$. The failure rate x is shown in Fig. 3 (a), where we randomly set three defaulting participants, 11, 37, and 47; each dot represents the failure rate of the participant in each time slot. The total amounts of negawatt energy s_j $(j = 1, 2, ..., 24)$ are shown as Fig. 3 (b). The condition $x_{k(t)} = 0$ in Theorem 1 holds for $t = 12$, which finished the algorithm in the twelfth iteration and provided the estimated result $\hat{x} = x(12)$ as shown in Fig. 3 (c). We see that the estimation in Fig. 3 (c) is equal to the true failure rate in Fig. 3 (a). This result demonstrates that the proposed algorithm exactly estimates the failure rate vector x with a small number of inspections.

5. CONCLUSION

In this paper, the detection of defaulting participants with time-varying failure rates has been investigated. By assuming that there are only a few defaulting participants and they default in all periods, we have proposed a detection algorithm based on block-sparse reconstruction.



(a) Failure rates x_{ij}

(b) Total amounts of negawatt energy s_j

(c) Estimation of x_{ij}

Fig. 3. Results estimated by the proposed method

In addition, the stopping rule that enables us to solve the problem with a small number of inspections was presented. It can enhance consumer acceptance and reduce the communication costs of the aggregator.

In the next step, we will improve our method to reduce the number of inspections by incorporating additional prior knowledge.

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