Smart Households' Aggregated Capacity Forecasting for Load Aggregators Under Incentive-Based Demand Response Programs

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***Abstract*—The technological advancement in the communication and control infrastructure helps those smart households (SHs) that more actively participate in the incentive-based demand response (IBDR) programs. As the agent facilitating the SHs' participation in the IBDR program, load aggregators (LAs) need to comprehend the available SHs' demand response (DR) capacity before trading in the day-ahead market. However, there are few studies that forecast the available aggregated DR capacity from LAs' perspective. Therefore, this article proposes a forecasting model aiming to aid LAs forecast the available aggregated SHs' DR capacity in the day-ahead market. First, a home energy management system is implemented to perform optimal scheduling for SHs and to model the customers' responsive behavior in the IBDR program; second, a customer baseline load estimation method is applied to quantify the SHs' aggregated DR capacity during DR days; third, several features which may have significant impacts on the aggregated DR capacity are extracted and they are processed by principal component analysis; and finally, a support vector machine based forecasting model is proposed to forecast the aggregated SHs' DR capacity in the day-ahead market. The case study indicates that the proposed forecasting framework could provide good performance in terms of stability and accuracy.**

***Index Terms*—Aggregated capacity, home energy management system (HEMS), incentive-based demand response (IBDR), load aggregator (LA), smart household (SH).**

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NOMENCLATURE

Indices

t	Timeslot [min].
k	DR day k in the test datasets.
i	i^{th} customer who participates in the IBDR program.

Sets

$\boldsymbol{T}$	Set of timeslots.
$\boldsymbol{T_{DR}}$	Set of timeslots during the DR time duration.
$\boldsymbol{K}$	Set of DR days.
$\boldsymbol{I}$	Set of the actual number of customers who participate in the IBDR program.

Parameters and variables

λ	Daily fixed electricity price [$/kWh].
Δd	Amount of electricity consumption reduction [kWh].
d^{cont}	Contracted electricity consumption reduction [kWh].
Inc	Monetary reward [$/kWh].
$s(\mu)$	Logical variable.
$\text{req}(P_{t,i,k})$	Household's initial required electricity consumption at the time t [kW].
$P_{t,i,k}^{\text{baseline}}$	Customer baseline load at the time t [kW].
$P_{t,i,k}$	Customer actual load at the time t [kW].
Δt	Time resolution (15 min) [min].
t_{start}	Start time of DR event [min].
t_{end}	End time of DR event [min].
$P_{t,i,k}^{\text{shift}}$	Electricity consumption of shiftable appliance at the time t [kW].
$\text{req}(P_{t,i,k}^{\text{shift}})$	Initially required electricity consumption of shiftable appliance at the time t [kW].
$p_{i,k}^{\text{shift}}$	Rated power of the shiftable appliance [kW].

$\tau_{t,i,k}^{\text{shift}}$	Running time of the shiftable appliance from the time $t-1$ to t [min].
ΔT	Shifting time of the shiftable appliance [min].
$P_{t,i,k}^{Ine}$	Electricity consumption of inelasticity appliance at the time t [kW].
$\text{req}(P_{t,i,k}^{Ine})$	Initially required electricity consumption of inelasticity appliance at the time t [kW].
$P_{t,i,k}^{\text{air}}$	Electricity consumption of the air conditioner at the time t [kW].
p_i^{air}	Rated power of AC [kW].
θ_{room}^t	Room temperature at the time t [°C].
C	Equivalent heat capacity [kWh/ °C].
R	Equivalent thermal resistance [°C/kW].
Q_i	Equivalent heat rate [kW].
θ_0	Ambient temperature [°C].
θ_{set}	Temperature set-point air conditioner [°C].
θ_{db}	Temperature dead bandwidth [°C].
$\Delta\tau_{\text{on},i,k}$	Time duration when the AC is ON [min].
$\Delta\tau_{\text{off},i,k}$	Time duration when the AC is OFF [min].
α	$\alpha = -1$ when in summer, $\alpha = 1$ when in winter.
η	Energy efficiency ratio of the AC
$\tau_{t,i,k}^{\text{air}}$	Time duration when the AC is ON from time t to t [min].
$f_{i,k}$	Individual customer DR capacity during the DR event [kWh].
f_k^{agg}	Actual aggregated DR capacity value in DR day k [kWh].
$\hat{f}_k^{agg}$	Forecasted aggregated DR capacity value in DR day k [kWh].

Abbreviation

SH	Smart household.
CBL	Customer baseline load.
CBE	Customer baseline energy.
HEMS	Home energy management system.
DR	Demand response.
PBDR	Price-based demand response.
IBDR	Incentive-based demand response.
RMSE	Root mean square error.
MAE	Mean absolute error.
APE	Absolute percent error.
MAPE	Mean absolute percent error.
MIC	Maximal information coefficient.
PCA	Principal component analysis.
SVM	Support vector machine.

I. Introduction

A. Motivation and Background

DEMAND response (DR) is a tariff or program which is established to motivate changes in electricity consumption [1]. It usually induces lower electricity use by electricity price [2] over time or incentive payments [3] when the grid reliability is jeopardized. It utilizes flexible demand-side resources to maintain the reliability of the power system [4] and significantly helps address the massive penetration of renewable energy resources [5] and other distributed generations [6].

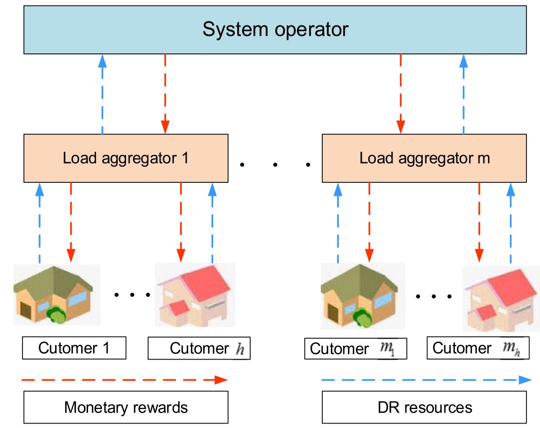

Fig. 1. Different roles under the IBDR program in the day-ahead market.

Residential customers are responsible for a considerable proportion of electricity consumption among all end-users and show considerable potential for DR [7]. However, only energy-intensive industrial and commercial end-users were traditionally permitted to participate in the incentive-based DR (IBDR) programs. On the one hand, individual residential customers possess a limited DR capacity which is unable to reach the capacity threshold of IBDR in the electricity market; on the other hand, residential end-users show heterogeneous characteristics [8], which make them a challenge for the system operator to manage directly. The emergence of load aggregators (LAs) [9] offers a solution to this problem because the LAs could act as agents for residential customers in the electricity market [10]. Hence, the system operator only needs to trade with the LAs instead of a large number of individual residential customers.

There will be an IBDR program in the electricity market when system operator calls for DR services [11] due to load shortage, penetration of distributed generations [12], and other reliability problem [13]. As shown in Fig. 1, the LAs procure the DR resources from residential customers by giving them monetary rewards and then provide these DR resources to the system operator. There is some essential information that the LAs need to figure out, one of which is the amount of DR resources, which is also called the "aggregated DR capacity." Accurate quantification and estimation of the available aggregated DR capacity prior to the DR event is significantly critical when LAs are trading in the day-ahead market [14]. However, it is usually a complex challenge to quantify and estimate the aggregated DR capacity prior to the DR event. Residential customers' electricity usage is not only affected by DR signals, but their behavior can also play a significant role. Their behavior usually presents gaps between knowledge, the perception of weather conditions, attitudes, etc., which are difficult to model and forecast specifically. Therefore, it is an unavoidable and significant issue for LAs to understand and model the customers' responsiveness reasonably and thereby accurately quantifying and estimating available aggregated DR capacity in the day-ahead market.

B. Literature Review

There exist a broad literature and research effort concerning the residential customers' responsiveness under DR programs from different perspectives. Majority focus on price-based DR (PBDR) programs [15]. The impacts of time-of-use (TOU) price and critical peak price (CPP) on the residential users' power are studied in [16] according to a PBDR pilot study conducted in British Columbia, Canada. It finds that the implementation of certain control strategies on users would further significantly help reduce electricity consumption. An association rule mining based quantitative analysis framework is proposed in [17] in order to explore the impact of household characteristics on peak demand reduction under TOU price and find that the amount of peak demand reduction responding to price signals is affected by many different factors. The effects of the PBDR program on load forecasting are studied in [18]; it acquires the load datasets through a home energy management system (HEMS) and via the optimal scheduling [19] of appliances for smart households (SHs), considering an hourly varying price tariff scheme. Compared with the PBDR program, there are very few studies focusing on residential customers' responsiveness and DR capacity under the IBDR schemes. In order to obtain a full characterization of residential consumers' flexibility in response to economic incentives, an empirical methodology is presented in [20]. It models individual observed flexibility and provides a straightforward application of classification methods to partition the sample of customers into categories of similar flexibility. However, it fails to evaluate the flexibility in aggregation level and is not able to consider the effect that customers' responsiveness may vary from one DR event to another in different DR days.

C. Contribution

Considering accurate information on the amount of the aggregated DR capacity is crucial for LAs in the day-ahead market trading, this article proposes a forecasting model to forecast the aggregated DR capacity for LAs under IBDR program in the day-ahead market. The contributions of this article are summarized as follows.

1) To our best knowledge, there are few studies that forecast the aggregated DR capacity from LA's perspective. This article proposes a method based on a machine learning mechanism to forecast the aggregated SHs' DR capacity from LA's perspective under IBDR programs in the day-ahead electricity markets.
2) Several factors that may have significant influences on the aggregated DR capacity forecasting are comprehensively identified and studied in this article, and several features are extracted as the input of the proposed forecasting method. It should be noted that the extracted features are not related to customers' privacy.
3) The principal component analysis (PCA) is employed to process the extracted features in order to reduce the redundant information between these features and help to improve the forecasting performance.
4) The effectiveness of the proposed method is verified by comparing it with the other two methods in the numerical case study.

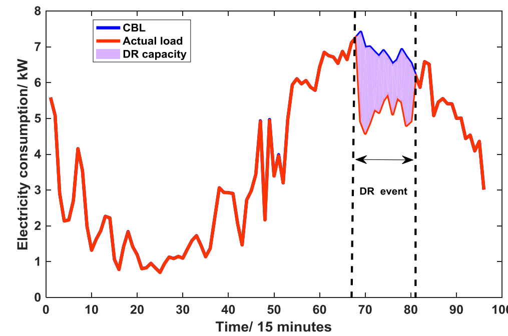

Fig. 2. Schematic diagram of the DR capacity.

D. Paper Organization

The remainder of this article is organized as follows. In Section II, the problem description and a basic idea of the proposed framework are explained. Section III presents how to model customers' responsiveness. In Section IV, a forecasting model is proposed and mathematically elaborated. The numerical case study is carried out in Section V. Finally, the conclusion is given in Section VI.

II. Problem Statement and Proposed Framework

A. Problem Statement

1) DR Capacity: In this article, the DR capacity is defined as the customers' ability to adjust electricity consumption during the DR event, and only the downward signals in the peak electricity usage time are considered in this article. The DR capacity can be assessed through the customer baseline load (CBL) [21] and the actual loads demonstrated by an individual customer in Fig. 2.

2) CBL Estimation: The CBL refers to the amount of electricity consumption that would have been consumed by the participants in the absence of the DR event. It has been widely studied and used in many different works [22]. It is introduced to quantitatively assess the DR capacity in this article. The difference between the CBL and the actual load is regarded as the DR capacity. Generally, a CBL estimation method should be simple enough for all stakeholders to understand, assess, and implement. Thus, a user-friendly and easy-to-understand average CBL estimation technique: HighX of Y is employed in this article. Additional details about High$X$ of Y are available in [23].

3) Mathematical Description: Let $\boldsymbol{T} = \{t|1, 2, \ldots, T\}$ be the set of timeslots in a day and $\boldsymbol{T}_{\mathrm{DR}} = \{t|t_{\mathrm{start}} \ldots t_{\mathrm{end}}\}$ be the set of timeslots during the DR duration time in a given DR day, where $\boldsymbol{T}_{\mathrm{DR}} \subseteq \boldsymbol{T}$ and the time resolution is $\Delta t = 15\,\mathrm{min}$ Furthermore, let $\boldsymbol{I} = \{i|1, 2, \ldots, I\}$ be the set of customers who participate in the IBDR program and $\boldsymbol{K} = \{k|1, 2, \ldots, K\}$ be the set of the DR days. For a customer i, let $f_{i,k}$ denote the DR capacity during the DR time duration in the DR day k, and f_k^{agg} represent the aggregated DR capacity of all customers who participate in the IBDR program in the DR day k. They could be mathematically expressed as

$$f_{i,k} = \sum_{t \in \boldsymbol{T}_{\mathrm{DR}}} (P_{t,i,k}^{\mathrm{baseline}} - P_{t,i,k}) \cdot \Delta t \tag{1}$$

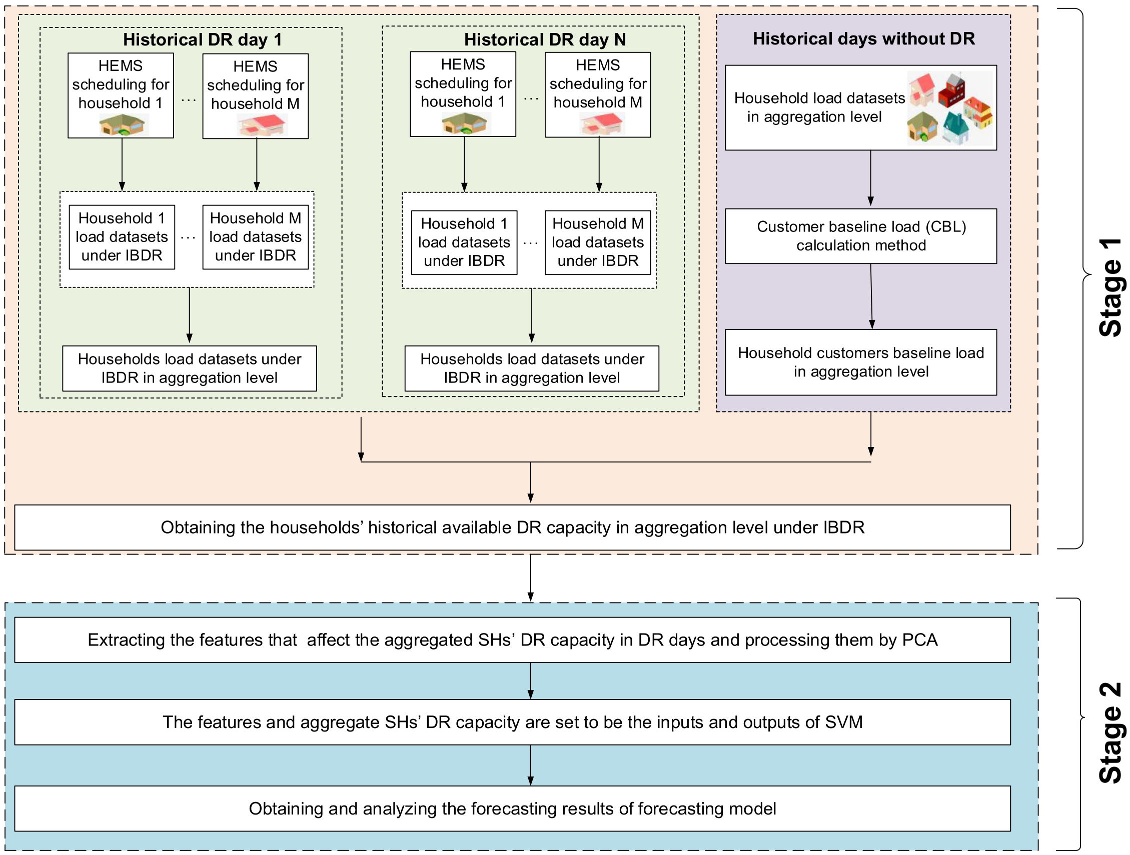

Fig. 3. Architecture of the proposed framework for aggregated DR capacity forecast.

$$f_k{}^{agg} = \sum_{i=1}^{I} f_{i,k} \tag{2}$$

where $P_{t,i,k}^{\text{baseline}}$ and $P_{t,i,k}$ denote the CBL and actual load, respectively, at timeslot t during the DR duration timet $\in \boldsymbol{T}_{\text{DR}}$. This article aims to formulate a forecasting model in order to forecast the aggregated DR capacity f_k^{agg} that the LAs could harness in response to a certain DR signal during the IBDR program in the day-ahead market.

B. Basic Idea and the Proposed Framework

There are two main challenges concerning the forecast of the aggregated DR capacity. The first challenge is to model the customers' responsiveness to DR signals and to acquire the customers' load data in the IBDR program because the actual residential customers' load data in IBDR programs are typically private and not readily accessible. The second challenge is how to accurately forecast aggregated DR capacity.

The issues listed above are addressed by two basic ideas: 1) this article focuses on SHs, and a model of HEMS [24] is applied to perform an optimal appliance scheduling and accordingly model the customers' responsiveness and obtain the customers' load data during the DR event in the IBDR program; and 2) the characteristics that influence the aggregated SHs' DR capacity are analyzed and nine features are extracted as the input of the forecasting model. In addition, a machine learning approach is employed as the forecasting engine for the aggregated DR capacity forecasting. The overall architecture of the proposed framework is illustrated in Fig. 3.

III. Modeling Customers' Responsiveness

A. HEMS Model for Smart Households Operation

HEMS has been widely deployed in the energy sector for several years. The HEMS could perform optimal scheduling of the electrical appliances primarily to shift and reduce the demand during DR events by considering several factors, such as DR signals, load profiles, and customers' comfort [25]. The HEMS architecture adopted in this article is a tool to model the customers' electricity consumption behavior under the IBDR program. Fig. 4 shows a schematic diagram of the smart household equipped with an HEMS. Distributed renewable energy is not considered in this article.

1) Objective Function: The objective is to minimize the individual customer's total daily cost of electricity consumption in the IBDR program. The objective function is shown as

$$\text{Minimize } F_1 = \sum_{t=1}^{T} \lambda \cdot P_{t,i,k} \cdot \Delta t - \text{Inc} \cdot \Delta d + \text{Pen} \cdot (d^{\text{cont}} - \Delta d) \cdot s(\mu) \tag{3}$$

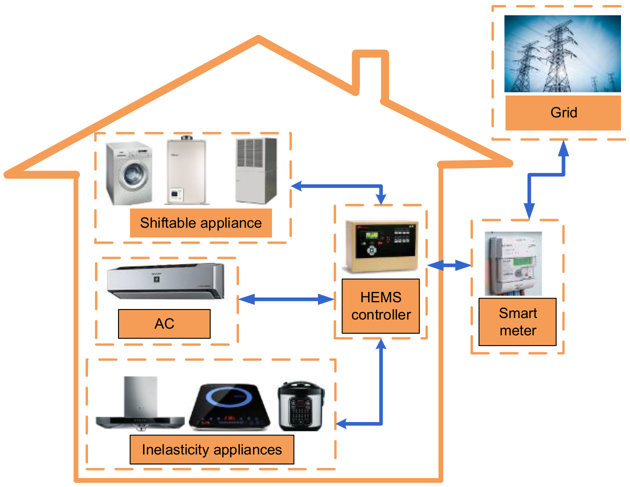

Fig. 4. Schematic diagram of the smart household.

where λ is the daily fixed electricity price. $s(\mu)$ is a logical variable that is used to judge whether the electricity consumption reaches the contracted level, thus knowing if the customer needs to pay for the penalty, and is shown as

$$s(\mu) = \begin{cases} 1 & \mu > 0 \\ 0 & \mu \leq 0 \end{cases} \quad \mu = d^{\text{cont}} - \Delta d \tag{4}$$

For a customer i in a DR day k, Δd represents the electricity consumption reduction (individual customer's DR capacity) during the DR event and is shown as

$$\Delta d = \sum_{t \in \boldsymbol{T}_{\text{DR}}} (P_{t,i,k}^{\text{baseline}} - P_{t,i,k}) \cdot \Delta t \tag{5}$$

where d^{cont} denotes the contracted electricity consumption reduction between the individual customer and the LAs, Inc is the monetary reward for unit electricity consumption reduction, and Pen is the monetary penalty for unit electricity consumption if individual customer's reduction does not reach to a pre-specified contracted level.

The following equation is used to judge if the customer will pay less compared to the circumstance without DR

$$F_2 = F_1 - \lambda \cdot \sum_{t=1}^{T} \text{req}(P_{t,i,k}) \cdot \Delta t \tag{6}$$

The main reason to add this equation is that the possibility of underestimation of CBL which could cause the underestimation of Δd, even the negative value of Δd. If the customers discover the unavailability to reduce the cost compared with the initial situation without participation in DR in day-ahead trading with LA, they will refuse to participate in that IBDR program.

The power balance constraints are enforced as

$$P_{t,i,k} = P_{t,i,k}^{\text{shift}} + P_{t,i,k}^{\text{air}} + P_{t,i,k}^{Ine} \tag{7}$$

where the total electricity consumption is made up of all shiftable loads $P_{t,i,k}^{\text{shift}}$, air conditioning (AC) $P_{t,i,k}^{\text{air}}$ and other inelastic loads $P_{t,i,k}^{Ine}$.

2) Modeling Shiftable Appliances: The shiftable appliances are considered as elastic loads. The electricity consumption of these loads could be shifted forward or postponed at a certain time interval and will not greatly affect the customers' comfort. When modeling shiftable appliances in the IBDR program, the optimized amount of shiftable loads should meet the initial requirements shown as

$$\sum_{t=t_{\text{start}}-\Delta T}^{t_{\text{end}}+\Delta T} (P_{t,i,k}^{\text{shift}}) = \sum_{t=t_{\text{start}}-\Delta T}^{t_{\text{end}}+\Delta T} \text{req}(P_{t,i,k}^{\text{shift}}) \tag{8}$$

where ΔT is the shifting interval under a certain incentive Inc at which the customer would like to modify the usage of the shiftable appliances. The power of the shiftable appliance at the time t is shown as

$$P_{t,i,k}^{\text{shift}} = p_i^{\text{shfit}} \cdot \tau_{t,i,k}^{\text{shift}} / \Delta t \tag{9}$$

where p_i^{shift} is the rated power of shiftable appliance and $\tau_{t,i}^{\text{shift}}$ denotes the running time of appliance from time $t-1$ to t, and must be no more than Δt, i.e.

$$0 \leq \tau_{t,i,k}^{\text{shift}} \leq \Delta t \tag{10}$$

3) Modeling the Air Conditioner: Air conditioner (AC) is an ideal appliance for the DR program as it does not need to be completely switched OFF during the DR event. The electricity usage could be modified by changing its temperature set points in an acceptable range. This article adopted a set of simplified equivalent thermal parameters (ETP) [26] in order to model the AC units. When the AC is turned ON, then the following constraint is enforced:

$$\theta_{\text{room}}^{\tau+1} = \theta_0^{\tau} + QR - (\theta_0^{\tau} + QR - \theta_{\text{room}}^{\tau}) e^{-\Delta\tau/\text{RC}}. \tag{11}$$

When the AC is turned OFF, we will then have

$$\theta_{\text{room}}^{\tau+1} = \theta_0^{\tau} - (\theta_0^{\tau} - \theta_{\text{room}}^{\tau}) e^{-\Delta\tau/\text{RC}} \tag{12}$$

where τ represents the resolution time of 1 min. The AC unit can only work at its rated power ${p_i}^{\text{air}}$ (ON) or 0 (OFF), which makes the indoor temperature change periodically within the range $[\theta_{\min}, \theta_{\max}]$ ($\theta_{\min} = \theta_{\text{set}} - \theta_{db}, \theta_{\min} = \theta_{\text{set}} + \theta_{db}$). Therefore, one is able to acquire the time duration of switching ON and OFF, which are shown as

$$\Delta\tau_{\text{on},i,k} = \text{RC} \ln \left(\frac{\theta_0^{\tau,k} - \theta_1 + Q_i R}{\theta_0^{\tau,k} - \theta_2 + Q_i R} \right) \tag{13}$$

$$\Delta\tau_{\text{off},i,k} = \text{RC} \ln \left(\frac{\theta_0^{\tau,k} - \theta_2}{\theta_0^{\tau,k} - \theta_1} \right) \tag{14}$$

$$Q_i = \alpha \eta {p_i}^{\text{air}} \tag{15}$$

$${P_{t,i,k}}^{\text{air}} = {p_i}^{\text{air}} \cdot \tau_{t,i,k}^{\text{air}} / \Delta t \quad \tau_{t,i,k}^{\text{air}} \in \Delta\tau_{\text{on},i,k} \tag{16}$$

$$0 \leq \tau_{t,i,k}^{\text{air}} \leq \Delta t \tag{17}$$

where θ_1 is set to $\theta_{\max}$, θ_2 is set to $\theta_{\min}$, and α is set to -1 in summer when the AC's cooling ability is needed. (This article takes AC's cooling mode as an example).

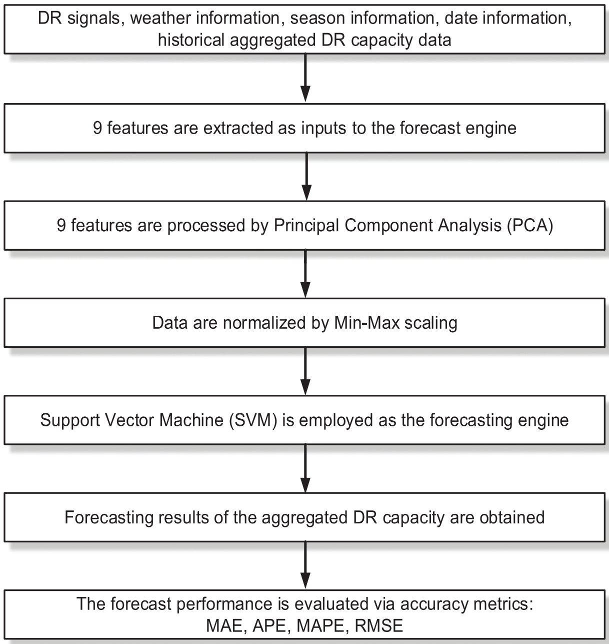

Fig. 5. Overall forecast structure.

4) Modeling Inelastic Appliances: In this article, the appliances that greatly affect the customers' daily habits and have little potential to reduce electricity usage are regarded as inelastic appliances. In such cases, any modification on the electricity consumption different from its regular usage habit could result in a significant violation of the customers' comfort zone. Thus, inelastic appliances are kept to their initially required electricity consumption and are not considered during the optimal operation of HEMS. It is shown as

$$P_{t,i,k}^{\mathrm{Ine}} = \mathrm{req}(P_{t,i,k}^{\mathrm{Ine}}). \tag{18}$$

IV. Forecasting Model

A. Forecast Engine: Overall Structure

After modeling the customers' responsiveness to the DR signals and acquiring the load data during the DR event in the IBDR program, the aggregated DR capacity in the historical DR days can be acquired. This section elaborates on how to forecast the available aggregated DR capacity, and the overall forecasting framework is shown in Fig. 5. It includes four main stages: 1) extracting the features that could capture the characteristics of aggregated DR capacity; 2) processing the features by the principal component analysis (PCA) in order to avoid noise and redundant information; 3) adopting the support vector machine (SVM) as the forecasting engine; and 4) evaluation of the forecast performance by accuracy metrics.

B. Feature Extraction

Customers' electricity consumption and DR capacity are affected by many different factors. So it is important to extract proper features as the input of the forecasting model so that a good forecasting performance can be obtained.

The features are extracted based on two principles in this article.

1) The features should affect aggregated DR capacity instead of just individual customers' DR capacity.
2) The features should be easy enough for LA to obtain in real life and not refer to customers' privacy as far as possible.

Therefore, the individual customer's household features, such as house size, type of dwelling, the number of occupants in the house, etc., are not considered in this article. The extracted features in this research are mainly categorized into the following two groups: 1) features that influence the daily aggregated electricity consumption. They are the highest and lowest temperature, as well as season label, weekday, and weekend labels in the upcoming DR day. 2) Features that decide how much electricity consumption the customers are willing to reduce on the basis of their daily electricity usage. These features mainly include the DR signals and related information, such as monetary reward, customer baseline energy (CBE, i.e., the initial electricity consumption under CBL during the DR event duration), DR start time, and duration in the upcoming DR day.

C. Principal Component Analysis (PCA)

PCA [27] is a mathematical transformation approach that converts a given set of related variables into another set of unrelated variables by the orthogonal transformation. The main role of PCA is to reduce noise and redundant data (i.e., dimensionality reduction) while preserving all critical information in the original dataset as much as possible. In this article, PCA is utilized to process the datasets and analyze the extracted features.

D. Support Vector Machine (SVM)

SVM is a statistical learning approach that can be applied to solve problems in nonlinear regression and forecasting. Unlike the classical neural networks, SVM formulates the statistical learning problem as quadratic programming with linear constraints through nonlinear kernels, offering a high generalization ability and solution sparsity. In addition, SVM has a better computational performance with a promising convergence. In this article, SVM is used as a forecasting engine for the day-ahead aggregated DR capacity forecasting.

E. Performance Metrics for Model Accuracy Evaluations

To assess the forecast performance of the proposed model, different error metrics are employed as the benchmark. The mean absolute error (MAE), the absolute percent error (APE), the mean absolute percent error (MAPE), and the root mean square error (RMSE) are widely used in forecasting and are given as

$$\mathrm{MAE} = \frac{1}{K}\sum_{k=1}^{K}\left|\hat{f}_k^{\mathrm{agg}} - f_k^{\mathrm{agg}}\right| \tag{19}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{K}\sum\nolimits_{k=1}^{K}\left(\hat{f}_k^{\mathrm{agg}} - f_k^{\mathrm{agg}}\right)^2} \tag{20}$$

TABLE I
PARAMETERS IN THE DR EVENTS

Base Fixed Tariff	0.3\$/kWh		
Monetary Reward	0.3\$/kWh	0.4\$/kWh	0.5\$/kWh
DR Event Time	12:00-14:00 17:00-19:00	12:00-15:00 17:00-20:00	13:00-15:00 18:00-20:00

$$\mathrm{APE} = \left| \frac{\hat{f}_k^{\mathrm{agg}} - f_k^{\mathrm{agg}}}{\hat{f}_k^{\mathrm{agg}}} \right| \tag{21}$$

$$\mathrm{MAPE} = \frac{1}{K} \sum_{k=1}^{K} \left| \frac{\hat{f}_k^{\mathrm{agg}} - f_k^{\mathrm{agg}}}{\hat{f}_k^{\mathrm{agg}}} \right| \tag{22}$$

where f_k^{agg} and $\hat{f}_k^{\mathrm{agg}}$ denote the actual and forecasted aggregated DR capacity values at the DR day k, respectively. The lower value of them means better forecasting performance.

V. CASE STUDY

A. Dataset

The data used in this research are from a real-world dataset: Pecan Street experiment in Austin, TX [28]. The dataset contains minute-resolution electricity consumption data from 500 homes (both the home-level and individually monitored appliance circuits). In order to consider the seasonal and yearly effect, this article chooses a two-year load data with a 1-min interval from January 1, 2015 to December 31, 2016. The data set is trimmed by removing the customers with missing load data, and finally, 170 customers with two-year load data are employed for the analysis.

B. Experimental Settings: Assumptions and Specifications

1) Selection of DR Days and DR Signal Settings: Since the load dataset only contains the residential customers' daily load data with no DR event, this article sets 65 DR days artificially in each year and assumes that each customer has an HEMS, which performs optimal appliances operation for each customer during DR events.

The DR signals are mainly related to DR start time, duration, and monetary rewards. As shown in Table I, there are three different types of monetary rewards and six different types of DR event times. In each DR event, monetary reward and DR event time are randomly selected accordingly, thereby leading to varying DR signals during different DR days.

2) Settings on Different Customer Types: In this article, two types of customers are studied, the sensitivity of which to the monetary rewards is different; specifically, one type pays more attention to the comfort level and willing to modify the electricity usage less (Type 1), and the other is willing to change the consumption habits to pursue cheaper electricity bills in the IBDR program (Type 2). Customer Type 1 and Type 2 are set to seven different proportions of all customers as presented in Table II.

After assumptions and settings, the 130-day customer load data under the IBDR program can be obtained through the modeling in Section II. The first 85 DR days' data are set for training, and the rest 45 DR days are set for testing for the forecasting engine.

TABLE II
PROPORTION OF TWO CUSTOMER TYPES UNDER DIFFERENT DISTRIBUTIONS

Customer Distribution	Customer Type 1	Customer Type 2
Distribution 1	0.2	0.8
Distribution 2	0.3	0.7
Distribution 3	0.4	0.6
Distribution 4	0.5	0.5
Distribution 5	0.6	0.4
Distribution 6	0.7	0.3
Distribution 7	0.8	0.2

3) Software and Parameters of the Proposed Method: The proposed method is implemented in Matlab, and the optimal problem is solved by the Yalmip toolbox in Matlab and solver Cplex for the Matlab interface.

As for parameters of SVM and constant values, they are listed as follows.

1) "s" = 3, "t" = 2, and "p" = 0.01.
2) "c" and "g" are obtained through grid search optimization.

C. Numerical Results and Analysis

In order to evaluate the accuracy and effectiveness of the proposed method, two benchmark methods are used in this article to make a comparison. The first method is the classical artificial neural network (ANN), which has been widely applied to different forecasting cases; the second one is a deep learning method: convolutional neural network (CNN), which is widely applied in many different research areas.

Different types of customers may have different sensitivity to DR signals. LAs, however, are usually not able to figure out details about that. What LAs need to understand is the circumstance in the aggregation level when participating in the day-ahead market. Therefore, the LAs seek a universal forecast of the aggregated DR capacity irrespective of the distribution of customers.

Table III presents the forecasting results of three methods with regards to MAE, MAPE, and RMSE under different distributions of customers. The better results are marked as bold. As it is shown in Table III, compared with the other two benchmark methods, the value of metrics of the proposed method is lower under most of the conditions. It indicates that the proposed method outperforms the other two forecasting methods when forecasting the aggregated DR capacity, and it also verifies the stability of the proposed method because the proposed method could show a good performance irrespective of the distribution of customers.

In addition, a comparison of the forecasted and actual values of aggregated DR capacity is presented in Fig. 6 (considering the length and layout of the paper, only the figures under distributions 1, 4, and 7 are listed). It can be seen intuitively in Fig. 6 that the forecasted value could consistently follow the trend of the actual value. It reflects a good fitting performance between the lines

TABLE III
COMPARISON OF THREE METHODS IN TERMS OF MAE, MAPE, AND RMSE UNDER DIFFERENT DISTRIBUTIONS OF CUSTOMERS

Customer Distributions		**MAE**	**MAPE**	**RMSE**
	ANN	31.7609	0.1622	40.9427
Distribution 1	Proposed method	**28.1653**	**0.1477**	**35.4016**
	CNN	31.5295	0.1605	39.7618
	ANN	32.3791	0.1638	40.9527
Distribution 2	Proposed method	**27.3701**	**0.1417**	**34.8597**
	CNN	30.6621	0.1581	38.6025
	ANN	30.0144	0.1538	37.5708
Distribution 3	Proposed method	**26.9967**	**0.1374**	**35.1978**
	CNN	28.1498	0.1489	35.7720
	ANN	29.0731	0.1458	37.8132
Distribution 4	Proposed method	**25.8484**	**0.1323**	**34.0790**
	CNN	28.3185	0.1463	36.1929
	ANN	29.3435	0.1473	39.4798
Distribution 5	Proposed method	**28.9893**	**0.1426**	**38.4267**
	CNN	29.3140	0.1446	38.5130
	ANN	**29.4248**	0.1497	**38.7549**
Distribution 6	Proposed method	29.5047	**0.1419**	39.2675
	CNN	29.7137	0.1454	39.5970
	ANN	30.9361	0.1441	41.3276
Distribution 7	Proposed method	**30.5032**	**0.1437**	40.7109
	CNN	30.5709	0.1463	**40.5525**

of forecasted and actual value under the different distributions of customers. Furthermore, the cumulative distribution of the APE in different DR days is shown in Fig. 7 (considering the length and layout of the paper, only the figures under distributions 1, 4, and 7 are listed). It reflects relative errors in all forecasting DR days. As it is shown in Fig. 7, the proposed forecast model could provide the aggregated DR capacity forecasting with over 90% accuracy for about 40% of the testing dataset and over 80% accuracy for over 70% of the testing dataset. The results mean that the proposed method is able to provide a good forecasting performance in the most DR days.

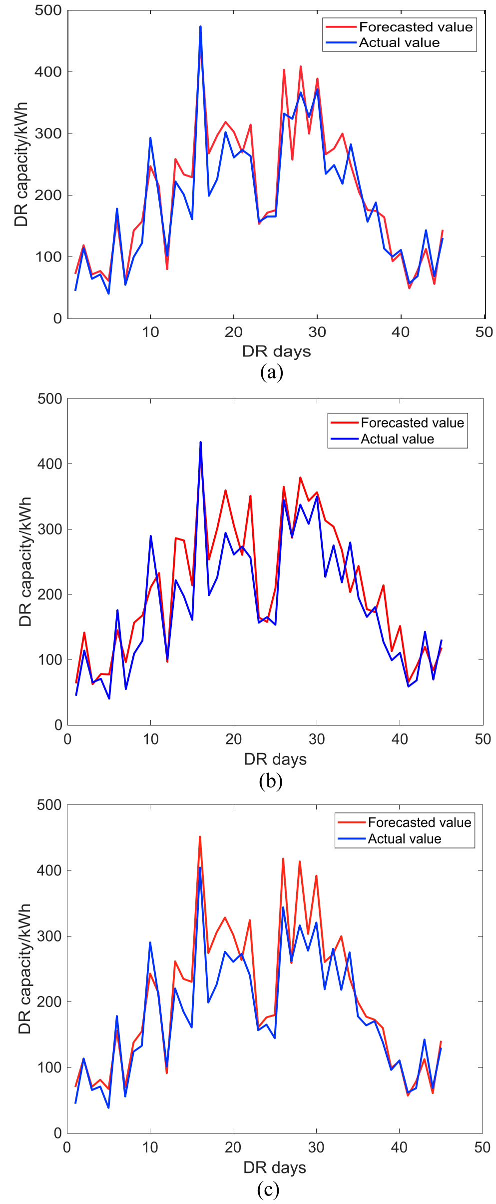

Fig. 6. Forecasting results: Comparison of the forecasted and actual values of the aggregated DR capacity under three different distributions of customers. (a) Distribution 1.(b) Distribution 4. (c) Distribution 7.

D. Discussions

In addition to the forecasting results that are presented earlier, this article will further explore how the forecasting performance is affected by 1) extracted features and 2) the number of customers.

1) Aggregated DR Capacity Forecasting and the Extracted Features: In order to explore the correlation between the extracted features and the aggregated DR capacity, the maximal information coefficient (MIC) [29], which has good performance in analyzing sophisticated relationships between variables (i.e., linear and nonlinear, functional, and nonfunctional), is employed. The higher the value of MIC means the greater influence and stronger correlation. The radar figure of MIC is shown in Fig. 8 (considering the length and layout of the paper, we only list the figure under distribution 4). It means the higher value of MIC when the feature is closer to the outside bound in Fig. 8. It is obvious that the CBE, temperature, monetary reward, and season label have a stronger correlation with the aggregated DR capacity.

This article ranks the features according to their values of MIC with the aggregated DR capacity (from 1 to 9 most correlative features). Based on the ranking results, this article lists the forecasting results in Table IV from two aspects: 1) under different numbers of features; and 2) with and without PCA processing. The better results are marked as bold. As illustrated in Table IV, if the features are not processed by PCA, the three most correlative features are found the best choices as the input to the forecasting model, while choosing all nine features would be preferred when PCA processing is adopted. Such a difference could be caused by the redundancy of input information. On the one hand, the increase in the number of features could offer more information in forecasting to help improve its accuracy to some extent; on the other hand, the additional number of features may result in information redundancy due to the coupling relationships that may exist in several features.

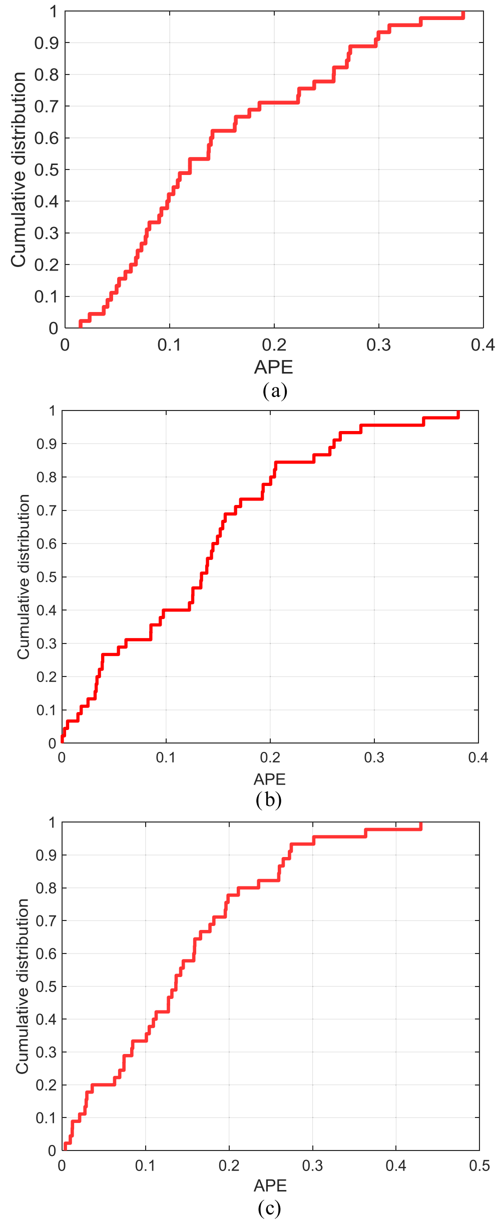

Fig. 7. Cumulative distribution of APE corresponding to the forecast results in different DR days under three different distributions of customers.

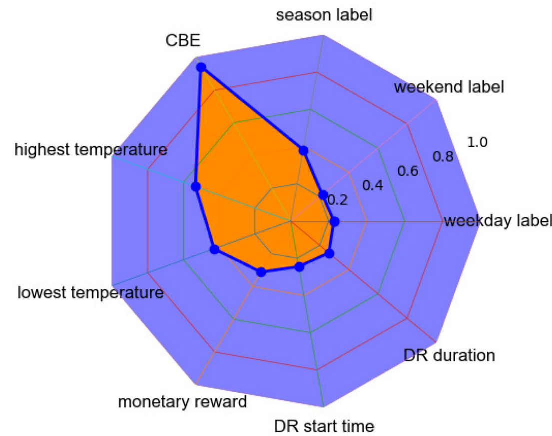

Fig. 8. MIC between nine features and the aggregated DR capacity.

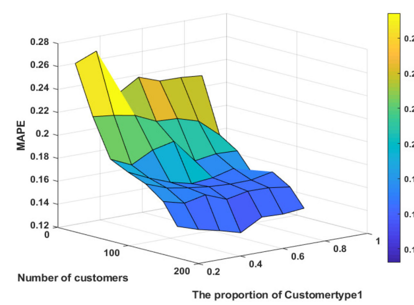

Fig. 9. MAPE on the forecast results under different number and distributions of customers.

TABLE IV
COMPARISON OF RESULTS WITH AND WITHOUT PCA PROCESSING ON DIFFERENT FEATURES

Number of features	MAE		MAPE		RMSE	
	No-PCA	PCA	No-PCA	PCA	No-PCA	PCA
1	38.9296	**38.9296**	0.1780	**0.1780**	51.1309	**51.1309**
2	**30.5665**	30.8505	0.1510	**0.1484**	**43.7043**	45.0578
3	**26.3856**	27.0816	0.1349	**0.1329**	**35.5612**	36.4180
4	31.7741	**27.2996**	0.1545	**0.1356**	41.9170	**36.6172**
5	35.8724	**26.9893**	0.1866	**0.1345**	46.4380	**36.1970**
6	31.3267	**27.2799**	0.1844	**0.1356**	40.6089	**36.5772**
7	29.3432	**26.3768**	0.1807	**0.1337**	36.4692	**34.8447**
8	31.1051	**25.9818**	0.1597	**0.1336**	39.3625	**34.1979**
9	36.4368	**25.8484**	0.1838	**0.1323**	45.0469	**34.0790**

2) Aggregated DR Capacity Forecasting and the Number of Customers: Different from MAE and RMSE, the MAPE is a relative accuracy performance evaluation metric. It takes an average over the APE in all forecasting DR days and suitable for exploring the impacts of the different numbers of customers on the overall forecasting accuracy. Fig. 9 shows the MAPE in all forecasting DR days under different numbers and distributions of customers. Note that different proportion of Customer Type1 in Fig. 9 reflects the different distributions of customers as defined in Table I. One can see that, irrespective of the distributions of customers, the MAPE shows a descending trend when the number of customers increases, i.e., the higher of the number of customers participate in the IBDR program, the lower forecasting errors could be obtained in all forecasting DR days.

Furthermore, the box-fit figures which describe the distribution of APE in all forecasting DR days under the different numbers of customers are illustrated in Figs. 10–12 (considering the length and layout of the paper, only the results under distribution 1, 4, and 7 are listed).

There are two main aspects which can be inferred from these figures: on the one hand, with the increase of the number of customers, the box-fit figures present a lower distribution of APE in all forecasting DR days; on the other hand, the descending trend is apparent when the number of customers is small, while it is stable when the number of customers is large. This highlights the fact that the more customers participate in the IBDR program,

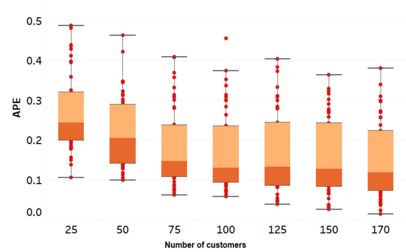

Fig. 10. Distribution of APE on the forecast results in all forecasting DR days under different number of customers in Distribution 1.

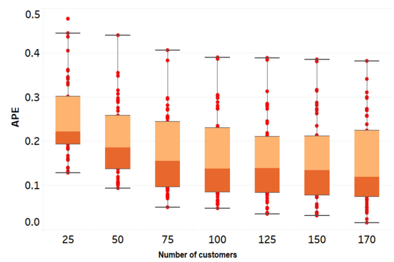

Fig. 11. Distribution of APE on the forecast results in all forecasting DR days under different number of customers in Distribution 4.

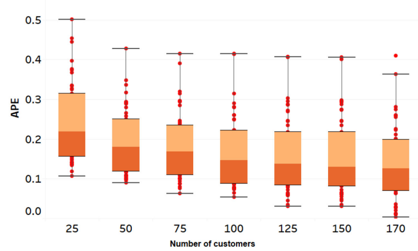

Fig. 12. Distribution of APE on the forecast results in all forecasting DR days under different number of customers in Distribution 7.

the lower forecasting errors could be achieved, which could reduce the risk when LAs (such as multiple ac microgrids under cooperative control [30]–[32] or a lot of HEMSs [33]) participate in the day-ahead market trading. These results could be explained with the following reason: if the LAs act on behalf of only a small number of customers in the IBDR program, then the fluctuation in the individual customer's electricity usage might greatly influence the aggregated DR capacity forecasts; however, once a considerable number of customers are willing to choosing the LAs as their agent to participate in IBDR program, such fluctuations in individual customer's electricity usage are limited and a more stable and accurate forecasting result could be obtained.

VI. Conclusion

This article presents a model based on the SVM to forecast the available aggregated DR capacity that the LAs could obtain from SHs under the IBDR program in the day-ahead market. It fills the gap that there are few related works. The effectiveness of the proposed method is verified by numerical results and analysis.

There are some conclusive results which could be summarized as follows:

1) Compared with the other two benchmark methods, the proposed method shows better performance and could provide a stable forecasting accuracy irrespective of distributions of customers.
2) PCA is helpful in processing features. If extracting the most suitable features is burdensome or not possible, then the PCA is suggested as a reasonable choice for processing the redundant information of the diverse features.

In addition, the impacts of the number of customers on forecasting results are considered, and it can be implied that if LAs want to pursue more accurate forecasting results in the day-ahead market trading, then they need to induce more customers to take part in the IBDR program.

Although some contributions are made in this article, there are still some research works that need to be done in the future. Future work can be summarized as follows.

1) The increasing distributed PV systems have been installed in the residential sector, and the impacts caused by additional PV penetrations on the aggregated DR capacity forecasting will be considered and explored in future work.
2) The details about LAs' trading and competition under IBDR programs in the day-ahead market will be further explored in future work.

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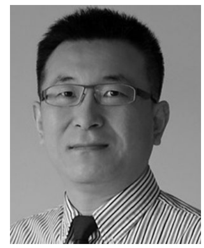

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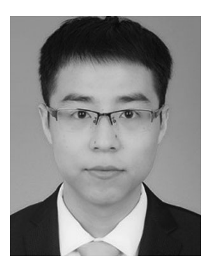

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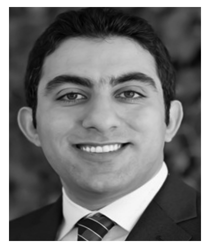

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