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A novel method for decomposing electricity feeder load into elementary profiles from customer information

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HIGHLIGHTS

- Use of aggregated electricity load profiles and customer description at feeder level.
- Statistical recovery of elementary load profiles with customer categorization.
- Generation of load demand profiles for unknown feeders and new local areas.
- Relevancy of the different categorizations.

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ABSTRACT

To plan a distribution grid involves making a long-term forecast of sub-hourly demand, which requires modeling the demand and its dynamics with aggregated measurement data. Distribution system operators (DSOs) have been recording electricity sub-hourly demand delivered by their medium-voltage feeders (around 1000—10,000 customers) for several years. Demand profiles differ widely among the various considered feeders. This is partly due to the varying mix of customer categories from one feeder to another. To overcome this issue, elementary demand profiles are often associated with customer categories and then combined according to a mix description. This paper presents a novel method to estimate elementary profiles that only requires several feeder demand curves and a description of customers. The method relies on a statistical blind source model and a new estimation procedure based on the augmented Lagrangian method. The use of feeders to estimate elementary profiles means that measurements are fully representative and continuously updated. We illustrate the proposed method through a case study comprising around 1000 feeder demand curves operated by the main French DSO Enedis. We propose an application o that uses the obtained profiles to evaluate the contribution of any set of new customers to a feeder peak load. We show that profiles enable a simulation of new unmeasured areas with errors of around 20%. We also show how our method can be used to evaluate the relevancy of different customer categorizations.

1. Introduction

1.1. Motivation

Electricity represented 18% of total final energy consumption in 2013 [1] and is expected to constitute a quarter of final energy consumption by 2040 [2]. 42% of global CO2 emissions in 2012, *i.e.* 13.8 gigatons of CO2, are due to electricity and heat production [3]. To reduce CO2 emissions due to electricity, many states are developing energy transition strategies. This kind of transition involves significant changes to electricity flows in the distribution network (with *e.g.* decentralized production, improved efficiency of buildings and appliances, new uses and demand response enabling energy consumption management [4]).

These changes impact the planning process of distribution system operators (DSOs). The current network planning process considers the two most extreme situations [5], *i.e.* maximum demand with minimum supply, and maximum supply with minimum demand. While planning with such a method does not require a deep modeling of the different dynamics and their correlations, it does not take into account the aggregation effect between supply and demand [6]. The above-mentioned changes make it necessary to model all of the aggregated demand dynamics.

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Nomenclature

a^f	consumption trend of feeder f relative to temperature	σ_k^2	empirical variance of $p_k^1, \dots, p_k^F$
b^f	temperature threshold of feeder f	T	number of instants
B	matrix of demand profiles of customer categories	t	instant
β	column vector associated with B	T^f	outside temperature of feeder f
c_k^f	annual consumption of category k for feeder f	u	vector $(1, \dots, 1)^\intercal$ of length K
d^f	demand of feeder f	v	vector $(T^{-1}, \dots, T^{-1})^\intercal$ of length T
d_k	elementary profile of customer category k	V_{inter}	inter group variability
ε^f	residual term for modeling feeder demand f	V_{tot}	total variance
F	number of feeders	X	matrix of feeder demands
f	feeder	x	column vector associated with X
K	number of customer categories	y	year
k	customer category	$\otimes$	Kronecker product
m_k	average demand share of a given category k		
p_k^f	share of electricity used by category k for feeder f		

1.2. Literature review

In this section we present two kinds of existing approach for modeling aggregated demand. The first is bottom-up, and uses individual customer profiles, which are summed to obtain aggregated demand. The second is a global approach in which the aggregated load curve is directly modeled using aggregated measurement data.

1.2.1. Bottom-up approaches

Measuring the electricity demand of individual electricity customers is a simple way to establish their load profiles and dynamics, and therefore a necessary step in bottom-up modeling. The current smart-meter roll-out in Europe will provide precise measurements of individual demand profiles. Around 80% of customers are scheduled to receive a smart-meter by 2020 [7]. However, this massive deployment is hindered by cost and privacy issues [8]. In 2014, only 23% of smart-meters in the European Union were installed in localized areas for private customers [9]. In some countries, this share is still insufficient to be representative, and the corresponding deployment is too recent to adequately cover long periods. To deal with the lack of individual measurements and characterize the behavior of electricity customers, researchers have attempted to classify them into different categories.

The classification of electricity demand profiles is a flourishing research topic (see reviews [10,11]). Researchers use individual measurements from smart-meters as input and apply different clustering methods [12]. This reduces the dimension, which makes it easier to manipulate data [13]. With the resulting classification, each customer is associated with a cluster and its corresponding load profile [14]. The classification and the obtained load profiles can be used for a number of applications.

First, a fine classification can be made in order to help decision-makers design personalized policies for specific customers [15].

Secondly, the classification allows a DSO to plan its network and anticipate its investments [16,17]. For example, the French DSO uses a model named "Bagheera" combining about 50 customer categories to plan its low-voltage network [5]. Classification is combined with the evolution of category distributions to forecast aggregated demand in prospective scenarios [18].

Last, classification and load profiles allow us to understand the contribution made by each category to aggregated demand [17].

Large measurement campaigns are necessary with these methods since a representative set of customers is required. This constraint makes continuous updating of the profiles difficult, which is an issue since it remains necessary to adapt the profiles to the changing consumption habits [19,14].

1.2.2. Global approaches

In global approaches, models forecast aggregated electricity demand with past measurements and explanatory variables, such as expected temperature or sometimes economic progress [20].

In order to obtain past measurements, most DSOs have been recording the electric power delivered by their medium-voltage feeders (around 1000—10,000 customers) for several years. These measurements are aggregated, but exhaustive, since all electricity customers' contributions are taken into account. This aggregated electricity demand data is considered as a "nonlinear, non-stationary series, and is often made up by a superposition of several distinct frequencies" [21] with daily to monthly periods in global models [22]. Additionally, the demand series can be divided into different parts (*e.g.* working time, holidays) [23,24].

The global approach produces accurate forecasts. However, these are based on aggregated past measurements, which are not available when planning a new unmeasured zone. This type of planning is improved with specific information about customers, which DSOs possess thanks to the Customer Information System (CIS) [16]. The CIS stores information on all customers regarding their electric connection to the grid, annual energy consumption, type of contract, and contracted power.

In all of the reviewed global methods [21] for modeling demand dynamics, the explanatory variables used, such as expected temperature or sometimes economic changes [20], do not characterize the feeder-specific local features. In particular, none of them employs CIS general statistics.

Finally, the drawback of these methods when used for planning purposes is that they cannot adapt to a change in the mix of customer categories. For example, in the case of the development of a commercial area in a residential feeder, such methods fail to take into account the corresponding information. If the profile differences of the two sectors is not accounted for, this might result in an overestimation of the future peak and hence an over-sizing of the network.

1.3. Contributions

Our paper presents a novel method to estimate elementary profiles. The proposed method relies on a statistical model that takes into account the mix of customer categories. To do this, we assume that the demands aggregate different shares of elementary profiles associated with different customer categories. These profiles are optimally found by minimizing prediction errors in a new algorithm relying on the augmented Lagrangian method.