Short Term Load Forecasting using Smart Meter Data

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ABSTRACT

Accurate short term electricity load forecasting is crucial for efficient operations of the power sector. Predicting loads at a fine granularity (e.g. households) is made challenging due to a large number of (known or unknown) factors affecting power consumption. At larger scales (e.g. clusters of consumers), since the inherent stochasticity and fluctuations are averaged out, the problem becomes substantially easier. In this work we propose a method for short term (e.g. hourly) load forecasting at fine scale (households). Our method use hourly consumption data for a certain period (e.g. previous year) and predict hourly loads for the next period (e.g. next 6 months). We do not use any non-calendar information, hence our technique is applicable to any locality and dataset. We evaluate effectiveness of our technique on three benchmark datasets from Sweden, Australia, and Ireland.

CCS CONCEPTS

• **Information systems → Clustering and classification**; • **Computing methodologies → Supervised learning by regression**;

KEYWORDS

Load Forecasting, SVD, Clustering, Data Transformation

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1 INTRODUCTION

A fundamental task in power planning is matching electricity supply with demand. Accurate demand forecasting is important for efficient management in the power sector. Both overestimate and underestimate of demand entail huge economic cost due to underutilization of installed generators, running peaker-plants or load-shedding. Also if load forecasting is done efficiently, this can help to perform soft load shedding [6]. Most of renewable energy resources are highly variable (spatially) and intermittent (temporally) in nature. Effectively integrating these resources in the grid requires load forecasts for short terms (one to a few hours) and at finer scales (one or a few consumers).

Recently, some work has been done towards short term load forecasting [3–5, 7]. These techniques either use some extra information (e.g weather, external surveys) to help increase the accuracy or at the end they report aggregate (sum) forecast error. However, our goal is to forecast hour ahead load at household level with high accuracy and without using any extra information.

Household level load forecast is significantly more challenging due to the interplay of many different factors. Most of these factors are very hard to measure (such as number and demographics of occupants, their daily schedules etc.) Moreover, there is an inherent stochasticity in how an individual or a household consumes energy. In this work, we use standard data analytics method of training and testing split to validate our results. We use one year of data the training set and next half year as testing. Our method does not take into account any non-calendar information about time or demographics information about households. This makes our method applicable to any region, type and number of households.

2 PROPOSED APPROACH

Let X be a $m \times n$ real matrix, where m is the number of hours and n is the number of consumers (households). We split X into two matrices A (training) and B (testing), containing the first m_1 (12 months) and the last $m_2 = m - m_1$ (6 months) rows of X, respectively. We use the following fundamental result from linear algebra

Theorem 2.1. *Let A be a $m \times n$ real matrix. There exists a factorization of A of the form $A = U\Sigma V^T$ such that: U is a $m \times m$ matrix of orthonormal rows, Σ is a diagonal matrix of non-negative real numbers, V is a $n \times n$ matrix of orthonormal rows*

The rows of U and V forms sets of orthonormal bases for the matrix M, essentially representing the hidden features (latent factors) on which the data varies the most. Singular value decomposition (SVD) is widely used in machine learning and statistics for dimensionality reduction by considering only the first few rows of U and

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V. These represent the most relevant features (incorporating the most variance in the data). This relevance of features are quantified by the singular values (Σ). In this work, we take the SVD of our training matrix $A = U\Sigma V^T$. Note that in our case m (the number of rows of A) is the number of hours in one year ($\approx$ 8760). While each hour is characterized by the consumption of n households (34, 709, 582 for Australian, Irish and Swedish data, respectively), this high dimensionality of data results in very inaccurate results. We thus take $d < n$ singular values and clusters hours by consumptions (i.e. rows of $U\Sigma$) into r clusters. Each of these r clusters contain hours that are substantially similar to each other and different from other hours (by consumption patterns not calendar values).

We consider an hour (a time-stamp/query time) as a 76-dimensional vector. The first 24 coordinates of this vector represent the hour of the day, the next 7 represent a day of the week, the next 31 represent day of the month. The following 12 coordinates stand for month of the year and the last two represent whether this hour is in a public holiday. We encode a given hour by the one-hot-encoding of its calendar attribute as given in Figure 1 (Top figure).

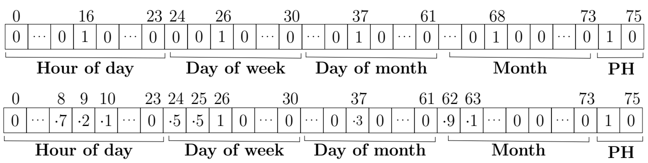

Figure 1: Vector encoding of an hour (Monday, July 7, 04:00 PM - 05:00 PM - non-public holiday "non-PH") and a cluster. The cluster contains 70% 8 AM, 20% 9 AM and 10% 10AM. Half of these hours are each of Mondays and Tuesdays. 90% of these hours are of January and remaining from February. Dates and public holidays are also shown.

A cluster of hours is also represented by a 76-dimensional vector with coordinates corresponding to the same attributes as for query time. More precisely, a cluster $C = \{h_1, h_2, \ldots, h_k\}$ of k hours is represented by $v(C) = \sum_{i=1}^{k} v(h_i)$, where $v(h_i)$ is the 76-d vector representing hour h_i. This vector is normalized by the sum of groups of coordinates described above. Figure 1 (Bottom figure) shows an example of a cluster with its vector encoding.

To predict consumption of household i at hour h, ($B(i, h)$), we find hours in the previous year that are similar to h and report household i's average in those similar hours. This is achieved by finding clusters of hours in the training set with highest similarity value, $s(h, c)$. The measure $s(h, c)$ is based on how many hours, days, months etc. are contained in cluster c that are nearby to the hour h.

3 EXPERIMENTS AND RESULTS

We use hourly consumption data from a city of Sweden [2], Australia [5] and Ireland [1]. There is a big right skew (majority are very low values) and variations in the data, because it is for very short duration. To deal with the high skew and significant fluctuations, we perform the standard nth root transformation on the datasets as a preprocessing step. The skew and effect of transformation is depicted in Figure 2. In experiments, we used $n = 3, 4, 5$ for Australian, Swedish and Irish datasets, respectively as the root. Note

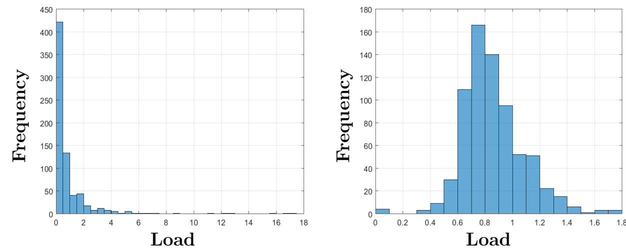

Figure 2: Customer loads histograms (Irish dataset) for one hour before and after transformation.

that we apply the corresponding reverse transform after prediction and report our forecasts and their error in the original units.

We used 34 singular values for Australian data matrix, since it has only 34 consumers (columns, an upper bound on its rank). For the other two matrices we use 400 largest singular values. Larger and smaller values did not show any significant difference. We cluster time-stamps into 80 clusters (using k-means++) for Swedish data and 70 clusters for the other two. Figure 3 depicts the vector encoding of three clusters of hours of the Irish dataset. We predict

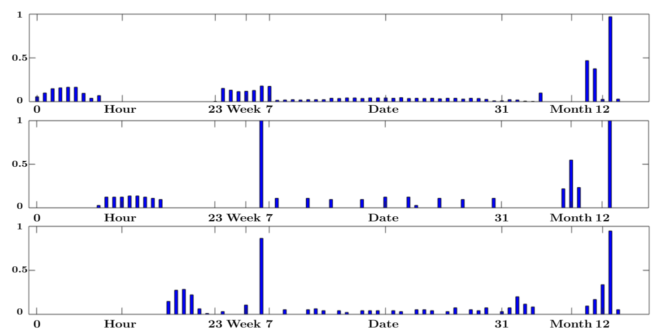

Figure 3: Bar graphs of vector encodings for three different clusters of time-stamps (for Irish datasets). The first cluster is of summer night hours, while the last one is for evening hours of winter weekends.

hourly load values of each household for the next six months. We computed the average errors over all hours for each household and report average of these averages. Table 1 shows the results.

Dataset	MAPE	MAE	RMSE
Sweden	32.2	2.4	1.7
Ireland	63.06	0.8	1.6
Australia	71.4	0.7	0.8

Table 1: Averages of per customer average errors.

4 CONCLUSION AND FUTURE WORK

We propose accurate short term load forecasting method at household level. We believe that combining our technique with existing methods in an ensemble based approach and utilizing weather information will prove to be very effective.

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