# CUSTOMER CLASSIFICATION AND LOAD PROFILING BASED ON AMR MEASUREMENTS

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## ABSTRACT

*Customer class load profiles are widely used in distribution network analysis. They are used, for example, in distribution network load flow calculation, state estimation, planning calculation and tariff planning. Previously, load profiling required expensive and time-consuming load research projects, but now automatic meter reading is providing huge amounts of information on electricity consumption. This paper presents different possibilities for utilizing AMR data on customer classification and load profiling. The customer classification and load profiling can be made separately or they can be combined by using clustering algorithms. Individual load profiles can also be formulated from the AMR measurements.*

## INTRODUCTION

Automatic meter reading (AMR) is becoming common in many European countries. In Finland, for example, distribution network operators (DNOs) are required to install AMR meters to at least 80 % of their consumption sites in their distribution networks by the end of 2013. Many DNOs plan to install AMR meters to all customers. AMR provides DNOs with accurate and up-to-date electricity consumption data. In addition to other functions, this data can be used to update load profiles and classify customers. The availability of AMR data also enables new and more accurate methods of modeling distribution network loads. Accurate load profiles are needed in daily used distribution network calculation, for example in load flow calculation, state estimation, planning calculation and tariff planning.

Distribution network customers are commonly classified to predefined customer classes, and the load of each customer is then estimated with customer class specific hourly load profiles. Currently, this method involves several error sources.

1) Sampling error. Parameters in the existing customer class load profiles can be based on measurements, which are misclassified or comprise an insufficient number of measurement points.
2) Geographical generalization. Load profiles are typically defined in national load research projects. Some of the accuracy is lost due to geographical generalization and within-country differences in electricity consumption are left unmodeled.
3) Profile drift. Electricity consumption is constantly changing but the load profiles are rarely updated.
4) Customer classification. DNOs have limited information on the type of the customers. The type of the customer is usually determined through a questionnaire when the electricity connection is contracted. However, the customer type may later change for instance because of a change in the heating solution.
5) Outliers. Some customers may have such an exceptional behaviour that they do not fit in any of the predefined customer class load profiles.

The above mentioned problems could be solved with the help of AMR measurements. The customer classification and load profiling could be done according to actual consumption data. Since AMR data is collected continuously, the classification and load profiles would remain up-to-date at all times. The classification and accuracy of the load profiles could be checked automatically for instance once a year. The load profiles could also be calculated separately for each DNO or region, thus avoiding the errors caused by geographical generalization. Outliers could be detected and individual load profiles could be formed for the outliers. Individual load profiles could also be calculated for some of the largest customers to improve the load estimation accuracy.

In this paper, we use real AMR data to update customer class load profiles and reclassify customers. Different classification methods, from simple reclassification to existing customer classes to K-means and ISODATA clustering (Iterative Self-Organising Data Analysis Technique), are tested. The results are compared with the original customer classification and load profiles. This paper shows that updated DNO specific customer class load profiles have a big effect on the accuracy of the load estimates. Furthermore, a method for forming individual load profiles for outliers or large customers is presented.

## BACKGROUND AMR DATA

Two different measurement sets from two Finnish distribution companies are used to study the different possibilities for utilizing AMR data on customer classification and load profiling. The first measurement set contains AMR measurements from 127 residential customers. These measurements cover the years 2006–2007. The second measurement set contains interval

measurements from 660 customers. All of these interval metered customers have annual energy consumption larger than 100 MWh/year. The measurement period for the interval metered customers was from 18 August 2008 to 31 December 2009. Both measurement sets have one hour measurement interval.
Here, the first year of measurement data is used for customer classification and load profiling and the rest of the data is used for the verification of the results. The residential measurements are used for load profile updating, reclassification, clustering and individual load profiling. The interval measurements are used for studying clustering and individual load profiles.
One year of measurement data is the minimum requirement for customer classification and load profiling. Better results are achieved if more data is available. However, if a lot of data is available, the possible changes in electricity consumption should be taken into account by weighting the most resent years or detecting change points.

## CUSTOMER CLASSIFICATION

Distribution system loads are commonly estimated with customer class load profiles. Each customer is linked to one of the predefined customer classes, and the load of each customer is then estimated with the customer class specific hourly load profile [1]. This method assumes that the distribution system operator knows which customer belongs to which customer class. In practice, classification errors are common.
AMR measurements can be used to improve the customer classification accuracy. Every customer with AMR can be classified according to its actual consumption by comparing the measured electricity consumption with the customer class load profiles or other customers. The customer classification can be made in many ways. The customers can be simply reclassified to the nearest existing customer class load profiles or new customer classes can be formed by grouping customers with similar behaviour. A simple reclassification procedure is defined and studied. Some test results are described in the following.

### Case 1: Customer reclassification

In customer reclassification, AMR measurements are used to determine which existing customer class load profile is closest to customer's true load pattern. Then the customer is reassigned to this customer class. The 127 residential customers studied in this paper are reclassified according to AMR measurements from the year 2006. Euclidian distance between the measurement and customer class load profile is used as a distance measure.

The studied customers were originally divided into six customer classes. They belonged to a network company which uses 38 customer classes. Table 1 shows how the customers were divided into the existing customer classes before and after customer reclassification.
After customer reclassification, the studied customers were scattered to 14 different customer classes. The accuracy of the customer classification was measured by using the customer class load profiles to make next day electricity consumption forecasts for the year 2007. Square sum of the forecast error was calculated for both original and new customer classification. Compared to the initial situation, the customer reclassification reduced the square sum of forecast errors by 7 %. The results can also be seen in Figure 1.
Here, as in the following cases, the outdoor temperature was taken into account with four season specific temperature dependency factors. The load profiles model the load in long-term average temperature. When making the next day load forecasts, the load was corrected according to the next day average temperature (forecast, in real applications).

## LOAD PROFILE UPDATING

Previously, load profiling required expensive and time-consuming load research projects and therefore the load profiles were rarely updated. Old load profiles and the constant change in electricity consumption habits have caused significant profile drift to the customer class load profiles. During the last decade the use of entertainment electronics has increased, heat pumps and air conditioners have become more common and lighting efficiency has increased, just to name a few changes.
AMR measurements could be used to update customer class load profiles. This would have several benefits. Regularly, for instance once a year, done load profile update would keep the load profiles up-to-date at all times. This would ensure that the load profiles keep up with the changing electricity consumption habits. Also, errors that are associated with sampling and geographical generalization would decrease. The sampling errors decrease when measurements from all or almost all customers are used in the load profile calculation. The geographical generalization could be avoided by calculating the load profiles separately for each distribution network area or region.

### Case 2: Load profile update

Load profile updating was studied here as an alternative to the customer reclassification. Six updated customer class load profiles were calculated for the 127 residential customers previously studied in case 1.

***Table 1.*** *Customer classification before and after customer reclassification.*

| Customers per customer class | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 10 | 11 | 15 | 26 | 28 | 30 | 31 | 38 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Original classification | 30 | 41 | 43 | 3 | - | - | 7 | - | - | - | - | - | 3 | - | - | - |
| Updated classification | 3 | 37 | 14 | 12 | 4 | 3 | - | 1 | 22 | 8 | 4 | 3 | - | 14 | 1 | 1 |

The load profile update was done with measurement data from the year 2006 using the original customer classification. As shown in Figure 1, the load profile update provided a 30 % reduction to the overall square sum of the forecast error.
The load profile update had a bigger effect on the load forecasting accuracy than the customer reclassification. The load profile update and the customer reclassification should of course be combined to achieve the best result. However, if the load profile update is done after the customer reclassification, the updated customer class load profile is no longer the nearest load profile for all customers. The customer class reassignment and load profile update should be done again and again until none of the customers change customer class during the reclassification process. Basically, this is a clustering problem. Clustering is studied in the next chapter.

## CLUSTERING

Clustering is an efficient technique for finding customers with similar behaviour. In literature, several different clustering methods have been applied to electricity customer classification [2], [3]. In this study, K-means and ISODATA clustering algorithms are used to solve the customer classification problem.
The clustering is done based on the AMR measurements, but since the hourly measurement data has a very high dimensionality, some kind of a dimension reduction is needed to speed up the computation and to get feasible results. There are many techniques for dimension reduction, for example principal component analysis, Sammon map and curvilinear component analysis [2]. Here, a pattern vector approach is used. The whole year's electricity consumption is described in a pattern vector containing average weekly loads for each calendar month. The pattern vector describes daily, weekly and monthly load variations on an hourly basis. In addition to 2016 hourly load values, the pattern vectors also include four customer specific temperature dependency parameters.
More information on the pattern vector formation and used ISODATA algorithm can be found in reference [4].

### Case 3: Clustering residential customers

Both K-means and ISODATA clustering algorithms were used to cluster the studied 127 residential customers into six customer groups. After clustering, new updated customer class load profiles were calculated for each customer class. Square sums of the forecast errors were calculated as before and the results were compared. K-means and ISODATA algorithms provided very similar customer classification accuracy. Figure 1 shows that both of these clustering methods reduced the square sum of errors by 36 % compared to the initial situation.
Classification accuracy was similar, but the K-means clustering was found out to be a lot simpler to execute than the ISODATA clustering.

### Case 4: Clustering non-residential customers

660 interval metered customers were used to demonstrate the clustering of non-residential customers. Before clustering the outliers were filtered from the data set. There is no point in trying to cluster customers whose electricity usage differs significantly from the other customers. Instead, individual load profiles can be formed for the outliers. Two stage statistical filtering was applied. The filtering was done based on monthly energy consumptions and Euclidian distances between pattern vectors. 92 customers were classified as outliers. More information on the used outlier filtering procedure can be found in reference [4]. No outlier filtering was done in Case 3 to keep the results comparable with Case 2.
The pattern vectors used in clustering were formed from measurements between 18 August 2008 and 17 July 2009.

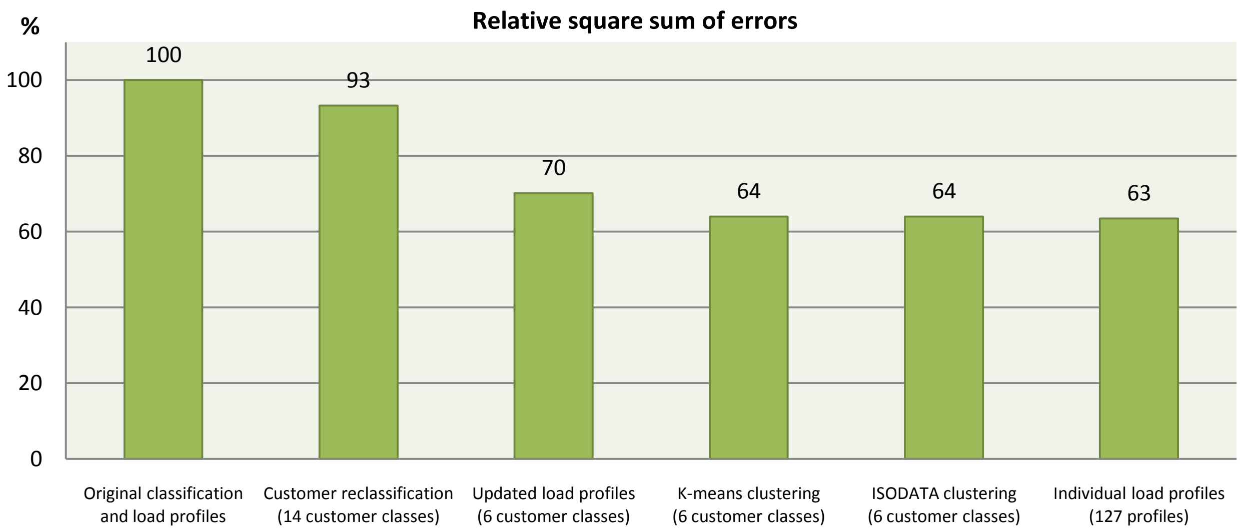


***Figure 1.*** *Square sum of the forecasting errors for 127 residential customers, in relation to the original situation.*

The 568 customers who passed the outlier filtering were clustered into 30 clusters and customer class load profiles were calculated for each cluster. Next day electricity consumption forecasts were made for the time period 18 August to 31 December 2009. The forecasting accuracy is later compared with the forecasting accuracy of individual load profiles in Figure 2.

## INDIVIDUAL LOAD PROFILES

Now that AMR measurements are commonly available, many DNOs are thinking of replacing the customer class load profiles with previous year's AMR measurements. In fact, the DNO that supplied the interval measurements for this study is already modeling interval metered customers that way. Previous year's measurements without temperature or special day correction are used as reference models in Figure 2.

When using measurements to model individual loads, we should take into account the facts that even consecutive years are not identical and individual loads are highly stochastic in nature. If the measurements are used for making load forecasts, the random variations in the weather and customers' hourly electricity consumption should be taken into account. The outdoor temperature can be taken into account with customer specific temperature dependency factors. In short-term forecasting the temperature forecasts can be used to adjust the load level and average temperatures can be used in long-term forecasts.

In current (Finnish) customer class load profiles the profiling errors and stochastic variations in hourly loads are described with standard deviation. The same approach should be applied also to the AMR measurement based individual load profiles.

In this study, individual load profiles are formed from measurements by calculating representative type weeks for each month. This method smoothes out the stochastic variations on hourly loads and enables the calculation of standard deviations. In type week, each day of the week is modeled separately. Holidays are modeled as Sundays.

### Case 5: Residential customers

Individual load profiles were formed for the 127 residential customers previously studied in Cases 1–3. As depicted in Figure 1, the forecasting accuracy of individual load profiles was only marginally better than the accuracy achieved with clustering and customer class load profiles.

### Case 6: Non-residential customers

With non-residential customers, the individual load profiles provided better results. The square sum of the forecasting errors decreased about 17 % compared to the clustering methods in Case 4. The type week based individual load profiles were 21 % more accurate than the load models based directly on the previous year's measurements. The results are also shown in Figure 2.

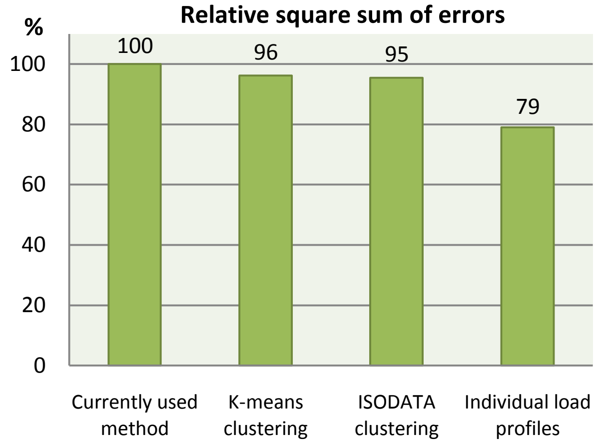


***Figure 2.*** *Relative square sum of the forecasting errors for 568 interval metered customers.*

## CONCLUSIONS

This paper compared different methods for utilizing AMR data on customer classification and load profiling. The simple customer reclassification to existing customer classes provided little improvement to the load profiling accuracy. Calculating updated DNO specific customer class load profiles was a much more efficient method to improve the load profiling accuracy. However, even better results were achieved by combining the customer reclassification and load profile updating with clustering methods.

The use of individual load profiles was also studied. When studying small residential customers, the individual load profiling improved the load profiling accuracy only marginally compared with the clustering methods. Only in the case of large non-residential customers, the accuracy improvement was large enough to make individual load profiling a viable option.

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