IMPROVING DISTRIBUTION NETWORK ANALYSIS WITH NEW AMR-BASED LOAD PROFILES

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ABSTRACT

Automatic meter reading (AMR) is becoming common in many European countries. This paper shows how AMR measurements can be used to create new load profiles and how these new load profiles can be applied to improve distribution network analysis accuracy. In this paper, hourly electricity consumption data is used to update existing load profiles, cluster customers and create new cluster profiles, and specify individual profiles for selected customers, all of which are then used in distribution network analysis. The results between existing and new load profiling methods are compared. Comparisons are also made between different methods of AMR-based load profiling.

INTRODUCTION

With the advent of smart grids, the ways of operating distribution networks are changing. The amount of distributed generation (DG) is increasing and in order to accommodate the intermittent DG with reasonable network investments, automatic control of networks is increased. For example, demand response and coordinated voltage control are developed to keep the line flows and voltages within acceptable limits. All this tightens the requirements set for distribution network analysis. In smart grids, network planning and operation must be made more carefully in order to keep distribution networks within reduced operating margins. This applies not only to medium voltage (MV) but also to low voltage (LV) networks. Distributed generation and active network control are spreading also to LV side [1].

The timely and spatially correct commitment of the demand response and coordinated voltage control require accurate information about the state of the network [2]-[3]. It has been shown that load profiles have a big effect on the accuracy of distribution network state estimation [3], [4]. When forecasting the future states of the network, the load profiles have an even bigger role. State estimates and forecasts have a crucial role in network operation, especially in smart grids, and more accurate load models are needed to improve them.

Making customer level load models used to be expensive and time consuming, but now that automatic meter reading is quickly becoming common in many European countries, the effort required for load research has decreased considerably. Modern AMR systems provide abundant amounts of information on customer level electricity usage. This, along with the defects in existing load profiles [5], has motivated us to improve load profiling accuracy with AMR-based load profiles.

In Finland, 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. In an earlier publication [5] it was proven that in this environment a simple yet efficient method for improving load profiling accuracy is to update the existing load profiles with the help of AMR measurements. Even better results can be achieved if the load profile updating and customer reclassification are combined with the help of clustering methods. Also, creating individual load profiles can be beneficial, especially for the largest customers.

In this paper, we will present a revised version of the AMR-based load profiling method introduced in [5]. The load profiles calculated with this method will be compared with existing load profiles and measurements.

MATERIAL AND METHODS

In this study, we used hourly AMR measurements from two Finnish distribution companies; Koillis-Satakunnan Sähkö (Case 1) and Elenia Networks (Case 2). The measurements from Koillis-Satakunnan Sähkö were made between the 4th of December 2007 and the 3rd of March 2011. The starting time of each measurement varied and only those customers who had been measured for at least 13 months were selected for further analysis. 5343 such customers were found from the measurement database. The developed load profiling method requires measurement data from at least one year. The last month from the measurement data was reserved for the verification of results. From Elenia Networks, we had 7558 measurements done between the 10th of June 2010 and the 31st of October 2012. The last year from the measurement data was reserved for the verification of results.

Both measurement sets came from small towns and rural areas surrounding the towns. These measurements covered a wide variety of customer types ranging from small summer cabins to large industrial customers. In Case 1, the measurements were scattered across the network operator's supply area in several municipalities. In Case 2, the measurements covered all the customers supplied by a substation feeding the town of Orivesi. For both cases, we had hourly temperature measurements and basic customer information. The original customer classification was known and network information enabled load flow calculations with original and new load profiles.

Figure 1 presents flow charts for the load profile updating and clustering methods used in this paper. After the measurements had been read and pre-processed, seasonal temperature dependency parameters were calculated for each customer using the method presented in [6]. The temperature dependency parameters were then used to normalize the measurements in to the long time average monthly temperatures. The temperature normalization was made so that measurements from several different years could be treated equally. Also, the normalized measurements were needed when the next year energy forecasts were made. If measurement data was available from several years, simple linear regression was used to forecast the next year's energy consumption.

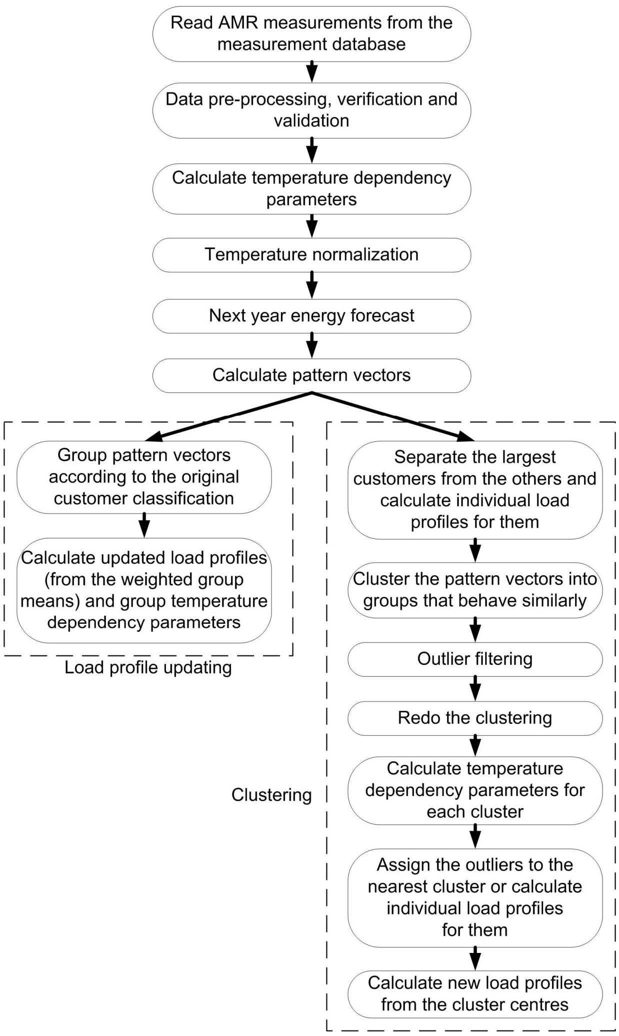

Figure 1. *Clustering and load profile updating methods.*

Pattern vectors describing the consumption of each customer were calculated from the normalized measurements. The pattern vectors consisted of 2016 values (12 months × 7 days × 24 hours = 2016) describing the average hourly consumption. Analysis of variance (ANOVA) was applied to determine if intraday behaviour on different weekdays was significantly different. If it was, then each weekday was modelled separately. If it was not, then all weekdays were modelled with a common weekday model.

At the beginning of the clustering procedure, the largest customers were separated from the others and individual load profiles were calculated for them. Then the pattern vectors were grouped into groups that behave similarly with the help of k-means clustering method. The original customer classification was used as a starting point for the clustering and pattern vectors were weighted according to the corresponding customer size (yearly energy). After this initial clustering, outliers were removed from the data. The customers with largest weighted distance from the cluster centres were selected for individual profiling and the customers with largest un-weighted distance were labelled as outliers and set aside (5 % of the total population). The clustering was redone and temperature dependency parameters for each cluster were calculated. Then the previously removed outliers were assigned to the nearest cluster and load profiles were formed from the cluster centres. Both the updated load profiles and cluster profiles were made compatible with the existing load profile format where each hour of the year has an expectation value and a standard deviation.

RESULTS

Case 1: Koillis-Satakunnan Sähkö

With the available AMR measurements, we were able to update 23 out of 38 customer class load profiles currently used in Koillis-Satakunnan Sähkö. Clear changes were observed in all the updated load profiles. Figures 2 and 3 show how the load profile for customer class 1 (housing) changed. From Figure 3, we can see that when the outdoor temperature is close to the average monthly temperature, the customer class sum load forecasted with the updated load profile matches to the measured sum load but when the temperature drops, the measured load exceeds the forecasted load. This is why we calculated temperature dependency parameters for each updated customer class. Temperature dependency information is especially useful when one is making short term load forecasts and temperature forecasts are available.

In distribution network analysis, one of the most important tasks is the forecasting of next year's peak loads. Temperature dependency information can help in this task; even it is not possible to make temperature forecasts so far ahead. Based on historical weather information, it is possible to determine a probable

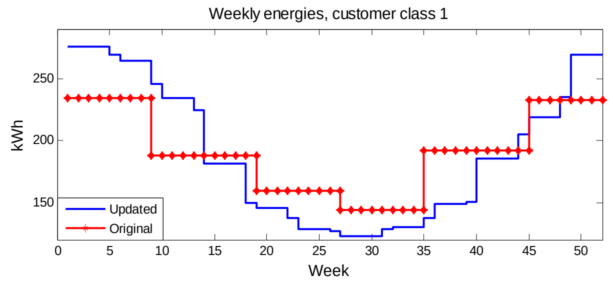

Figure 2. *Comparison of weekly energies in original and updated load profile.*

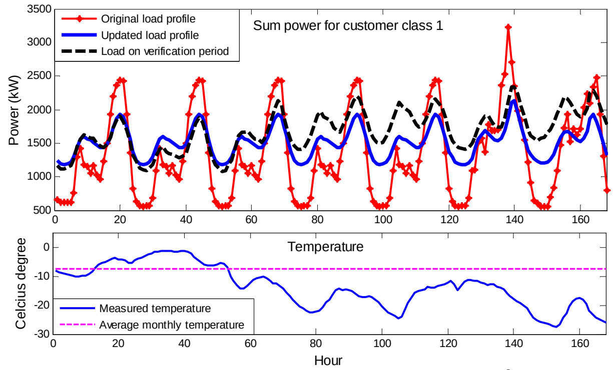

Figure 3. *Customer class 1 sum power for 2nd week of February.*

minimum temperature for a certain area to make "worst case" simulations. For areas studied in this paper, −25 °C was a good estimate for minimum daily temperature.

During the clustering phase, the customers were clustered in to 27 clusters and 100 individual load profiles were formed for large and abnormally behaving customers. The original customer classification was used as a starting point of the clustering but the final customer classification had little to do with the original customer classification. Only 15 % of the customers stayed in their original customer classes.

Since all customers are not (yet) measured with AMR and optimal clusters can be determined only for measured customers, the old and updated load profiles have to be used side by side with the cluster and individual profiles in network calculation. During this study, a modified prototype version of ABB MicroSCADA Pro DMS 600 -software was made to test this concept. The prototype software used all the aforementioned load profile types together. Old and updated load profiles were used for the unmeasured customers and cluster and individual profiles were used for the measured customers. Also, the operator could choose which load profiles to use. The prototype software was used first for LV network minimum voltage analysis but no clear differences between the load profiling methods were detected due to the stochastic nature of LV loads. The differences can be seen only when studying aggregated loads or when the sample size is large enough.

Table I shows average peak loads for all 5343 studied

Table I. *Comparison of peak load estimates on a customer level.*

Method	Average peak load (kW) confidence level		
	50 %	90 %	95 %
Original load profiles	4.2	7.0	7.8
Updated load profiles	3.5	5.9	6.6
Updated load profiles -25 °C	4.1	6.4	7.1
Cluster profiles	3.8	5.8	6.4
Cluster profiles -25 °C	4.4	6.4	7.0
Peak load on a previous year	7.0		
Measured peak load on the verification period	7.17		

customers. When using 95 % confidence level, which is a typical confidence level when calculating peak loads, the original load profiles give too high peak load estimates but the updated load profiles and cluster profiles give good results when −25 °C minimum temperature is assumed (minimum temperature during the verification period was −26 °C).

Case 2: Elenia Networks

In Case 2, updated load profiles were calculated for 30 customer classes. As in Case 1, the updated load profiles gave significantly lower peak load forecasts than the original load profiles but when scaled to estimated yearly minimum temperature of −25 °C, the peak load forecasting accuracy improved.

In the clustering phase, the customers were clustered in to 30 clusters and 200 individual load profiles were formed for large and abnormally behaving customers. With the updated load profiles, the verification period square sum of forecasting errors decreased 38 % when compared with the original load profiles. With the cluster profiles this value was 57 %.

Tables II and III show verification period peak load forecasts calculated on a distribution transformer level (i.e. sum of all the customers supplied by the specific transformer) and on a substation level. On average, the best distribution transformer level peak load forecasts

Table II. *Comparison of peak load estimates on a distribution transformer level.*

Method	Average peak load (kW) confidence level		
	50 %	90 %	95 %
Original load profiles	44.7	57.9	62.0
Updated load profiles	36.6	44.9	47.5
Updated load profiles -25 °C	47.8	55.9	58.4
Cluster profiles	39.1	46.2	48.6
Cluster profiles -25 °C	50.5	57.4	59.7
Peak load on a previous year	56.8		
Measured peak load on the verification period	53.7		

Table IV. *Comparison of peak load estimates on a substation level.*

Method	Peak load (MW) confidence level		
	50 %	90 %	95 %
Original load profiles	17.3	17.8	17.9
Updated load profiles	15.1	15.3	15.4
Updated load profiles -25 °C	19.8	20.0	20.1
Cluster profiles	15.0	15.2	15.2
Cluster profiles -25 °C	19.8	19.9	20.0
Peak load on a previous year	19.9		
Measured peak load on the verification period	19.3		

were achieved using updated load profiles and 90 % confidence level. Also, the original and cluster profiles provided good results with 90 % confidence level. The selection of the best confidence level proved to be difficult since for small distribution transformers with few customers the 95 % confidence level provided the best results but for large distribution transformers with many customers the 50 % confidence level was the best. On the substation level peak load forecasts the effect of used confidence level was small and the selected minimum temperature dictated the peak load forecast magnitudes. In Case 2, the forecasted peak loads were systematically higher than the actual measured peak loads since there was a 6.8 % drop in the electricity consumption between the load profile identification and verification years. This drop could not be explained entirely with load temperature dependency and was probably caused by economic factors which were not taken into account in this study.

CONCLUSIONS

This paper presented two alternative methods for calculating AMR based load profiles. The first method used AMR measurements to update the existing customer class load profiles but kept the customer classification unchanged, while the second method used k-means clustering to update both the load profiles and customer classification. Also, individual load profiles were formed for large and abnormally behaving customers. Both the presented load profiling methods modelled the load temperature dependency and random variation separately.

Load temperature dependency information is especially useful when one is making short term load forecasts but it can be used to improve next year peak load forecasts as well. In cold countries, the peak loads occur during the coldest days of the year and it is quite easy to determine a suitable peak load calculation temperature from the historical temperature information.

The new AMR based load profiles were clearly better than the original load profiles. When forecasting future loads, the cluster profiles had the best average fit but no significant improvement in peak load forecasting capability was detected when compared with the updated load profiles.

Although the results were better than with the original load profiles, the customer and distribution transformer level peak load forecasting proved to be a challenging task even for the new AMR based load profiles. Since the previous year's peak load seems to give a good indication for future peak loads, the direct usage of AMR measurements in distribution network peak load calculation should be studied. Also, the possibility of using distribution transformer level load models, instead of aggregated customer level load models, in MV network calculation could be studied.

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