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Case Studies on Using Load Models in Network Calculation

Revision History

Edition	Date	Status	Editor
v0.1	10.10.2012	Created	A. Mutanen
V1.0	13.12.2012	1st version	A. Mutanen

Abstract

This report shows how new AMR-based load profiles – created in SGEM Task 4.2.1 “Novel load modelling methods using new available data” – can be used to improve distribution network analysis accuracy. Measurement data from automatic meter reading (AMR) system is used to create new load profiles 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.

Contents

1 Preface

This report was done as a part of the Finnish national research project "Smart Grid and Energy Market" SGEM. It was funded by Tekes – the Finnish Funding Agency for Technology and Innovation and the project partners.

This report shows how new AMR-based load profiles – created in SGEM Task 4.2.1 “Novel load modelling methods using new available data” – can be used to improve distribution network analysis accuracy. The case studies in this report will be limited to the analysis of load forecasts and load flow results. The originally planned case studies with state estimation calculation were delayed and will be presented in a later publication.

2 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]-[4]. It has been shown that load profiles have a big effect on the accuracy of distribution network state estimation [4], [5]. 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 [6], 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 [6] 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 report, we will present a revised version of the AMR-based load profiling method introduced in [6]. The load profiles calculated with this method will be compared with existing load profiles and measurements. Comparisons are also made between different methods of AMR-based load profiling. The practical benefits of the proposed load profiling method will be shown with calculations done with distribution network analysis software.

3 Load profiling

This chapter describes the basic principles of the developed AMR-based load profiling method and introduces the measurement material used in this study.

3.1 Material

3.1.1 Case 1: Koillis-Satakunnan Sähkö

Hourly AMR measurements from Koillis-Satakunnan Sähkö Oy were used in this study. The used measurement set contained measurements from a time period between 4th of December 2007 and 3rd of March 2011. The starting time of each measurement varied and only those customers that 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. Measurements from the last month were reserved for verification and comparison of results.

Koillis-Satakunnan Sähkö Oy is a small distribution network operator supplying two small towns, Virrat and Ähtäri, in Western Finland. Koillis-Satakunnan Sähkö supplies electricity to almost 16 000 customers. The available measurement set represents 1/3 of the overall customer volume and contains all kinds of customers ranging from small summer cabins to large industrial customers.

Hourly temperature measurements from Virrat were also available. Since the distance between Virrat and Ähtäri is less than 40 km, the same temperature was assumed for the both cities. Figure 1 show how the outdoor temperature affects to the sum of measured customers.

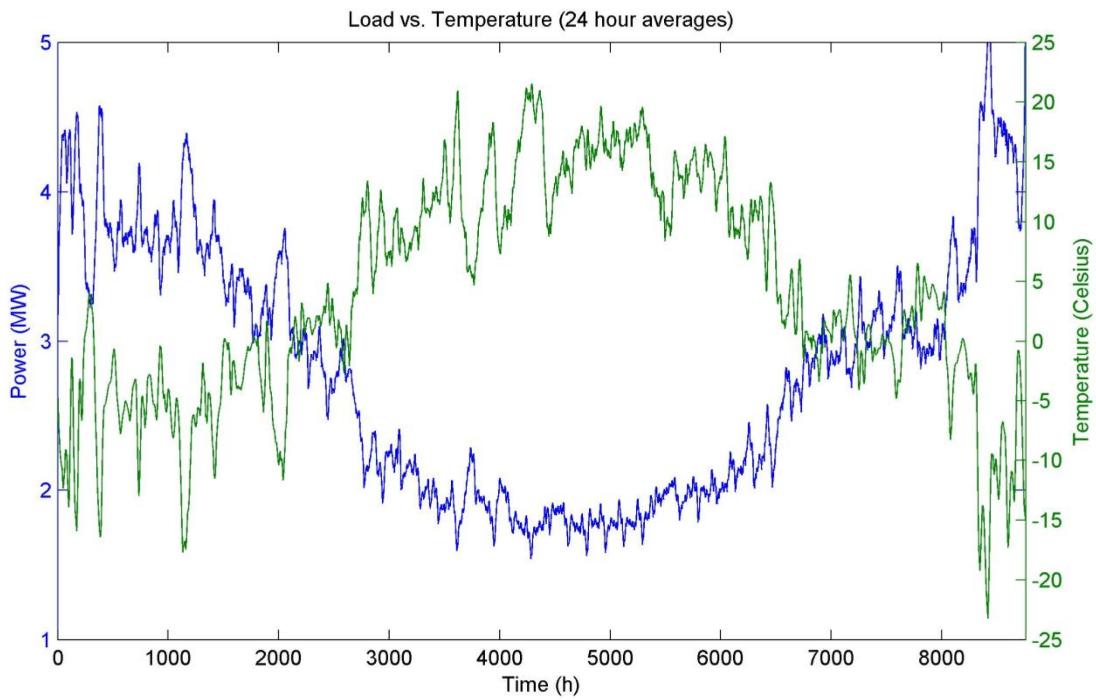

Figure 1. *Sum of measured loads and temperature for year 2009 (24 hour averages).*

In addition to the measurements we also had access to basic customer information. From customer information table we could see, for example, to which customer class each customer was originally classified, which load profiles was used to model them, what was their fuse size and tariff and what was the supplying distribution transformer. Furthermore, we had access to network information system with complete network model. This enables us to make load flow calculations with real network using the load profiles.

3.2 Load profiling method

Figure 2 describes the load profiling procedure that was used to make the AMR-based load profiles presented in this report. First, AMR measurements were red from the measurement database and saved in to a Matlab compatible data format. Matlab was used as a primary tool in load profiling. Next, a various degree of data pre-processing, verification and validation was needed in order to select valid measurements, correct errors and transform the timeseries into a uniform configuration.

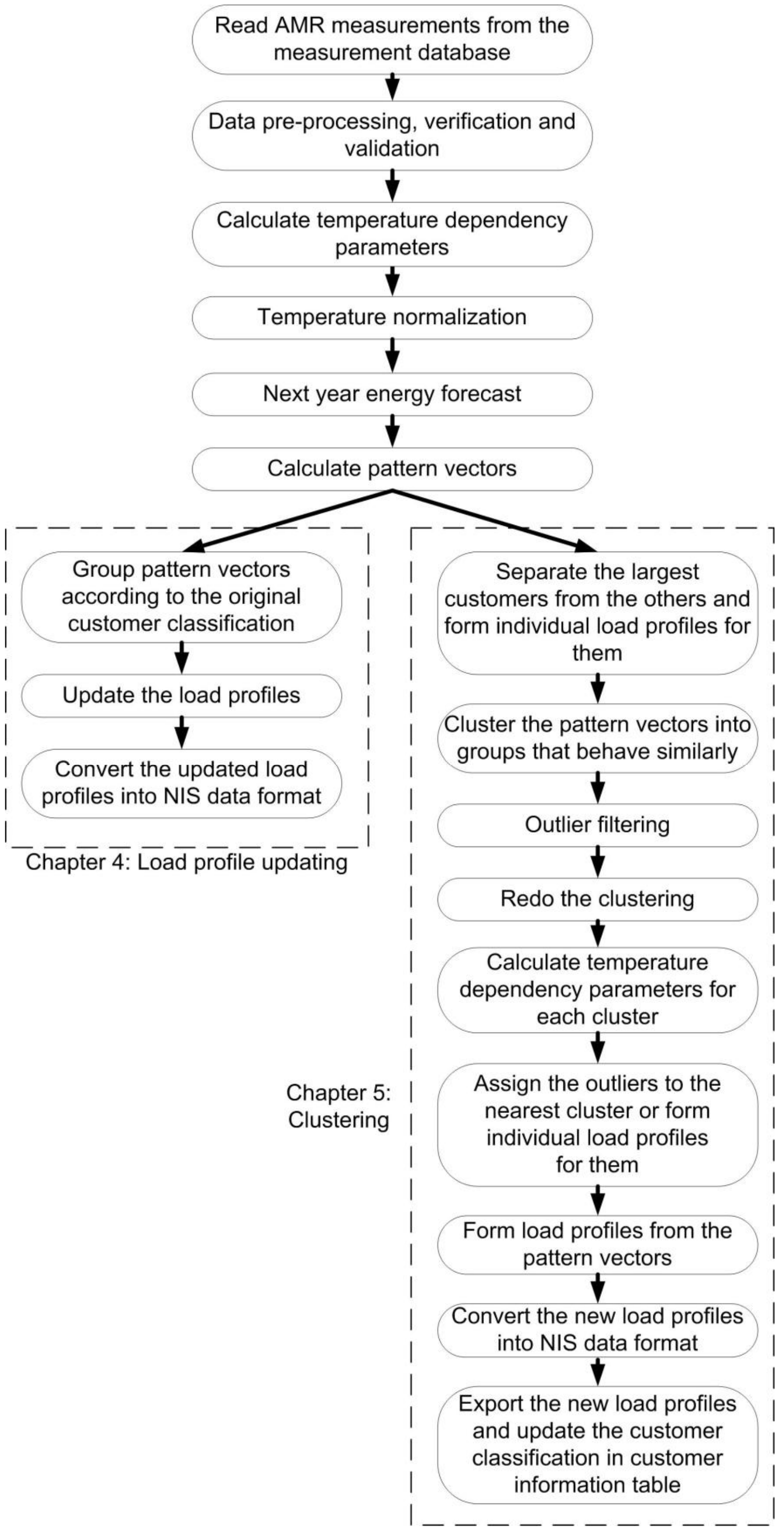

Figure 2. *Load profiling flowchart.*

The next step was the calculation of temperature dependency parameters. Seasonal temperature dependency parameters were calculated for each measured customer. The method for calculating temperature dependency parameters has been presented in [8]. 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 measurements data was available from several years, simple linear regression was used to forecast the next year's energy consumption.

Pattern vectors describing the consumption pattern of each customer were calculated from the normalized measurements. The pattern vectors consisted of 864 or 2016 values (12 months× 3 days×24 hours = 864 or 12 months×7 days×24 hours = 2016) describing the average hourly consumption. During the load profile updating Case 1, pattern vectors with 864 values were used and all weekdays were assumed to behave similarly. During the clustering, pattern vectors with 2016 values were used and analysis of variance (ANOVA) was applied to determine if weekdays were significantly different. If they were different, then each weekday was modelled separately. If they weren't, then all weekdays were modelled with a common weekday model.

When the load profiles were updated, the pattern vectors were first grouped according to the original customer classification and mean vectors for each customer class were calculated. Temperature dependency parameters for each customer class were also calculated. Then the mean vectors were expanded to cover the whole year (1990, which is used as a base year in load profiling) and normalized to 10 000 kWh yearly energy level. Finally, the updated load profiles were written into .bin files and exported to the network information system.

At the beginning of the clustering procedure, the N (where N is user selected value) largest customers were separated and individual load profiles were formed 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 N patterns with largest weighted distance from the cluster centres were selected for individual profiling and 5 % of the rest of the patterns were removed. The clustering was redone and temperature dependency parameters for each cluster were calculated. The previously removed outliers were assigned to the nearest cluster and load profiles were formed from the cluster centres. Finally, the new cluster profiles were written into .bin files, exported to the network information system and the customer classification was updated to correspond the clustering results.

4 Load profile updating

The easiest and most straightforward way of using AMR measurements to improve the distribution network calculation accuracy is the use them to update the existing customer class load profiles. The customers could also be reclassified with the help of the AMR measurements but in [6] it was proven that load profile updating has a much bigger effect on the load profiling accuracy. Simultaneous load profile updating and customer reclassification is possible only with the help of the clustering methods which are tested in Chapter 5.

4.1 Case 1: Koillis-Satakunnan Sähkö

Load profiles for Koillis-Satakunnan Sähkö Oy were updated with AMR measurements which were done between the years 2007–2011. Only 23 out of 38 customer class load profiles were updated because some customer classes didn't have enough measured customers. Only customer classes with more than 30 measurements or customer classes which had over 90 % of its customers measured were updated. Table I shows how many measurements there were from each customer class and which load profiles were updated (shaded rows). The total amount of measured customers was 5343 (out of 15764).

Table I. *Measurements available in this study.*

Customer class / profile	Number of measurement	Total number of customers
1	2179	7534
2	733	3008
3	211	617
4	54	166
5	56	185
6	42	295
7	566	659
8	666	778
9	10	390
10	1	11
11	4	134
12	0	11
13	9	196
14	3	26
15	4	55
16	0	37
17	59	118
18	337	676
19	49	119
20	12	13
21	8	53
22	0	0
23	55	134
24	3	34
25	5	8
26	2	2
27	10	41
28	193	238
29	5	5
30	53	147
31	2	2
32	1	1
33	1	1
34	1	1
35	0	3
36	1	1
37	3	5
38	1	1

The load profile updating changed the load profiles significantly. Figure 3 shows how the second week of January differs in some original and updated load profiles. Note that the figures start from Monday 07:00. Not only the intra-week models but also the weekly energy consumption models changed. Figure 4 compares weekly energies between original and updated load profiles.

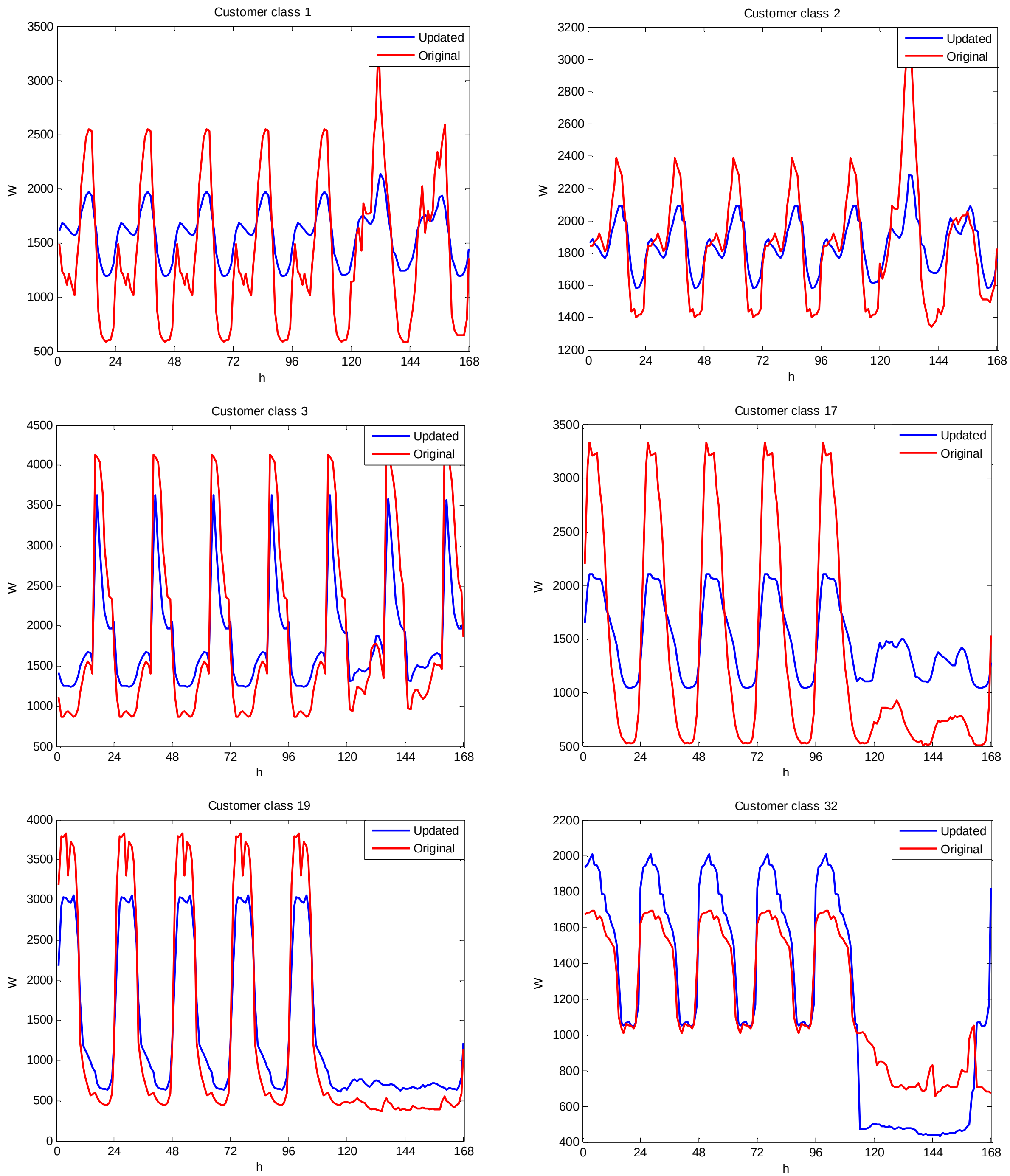

Figure 3. *Original and updated load profiles for customer classes 1 (housing), 2 (housing + direct electric heating), 3 (housing + partial electric storage heating), 17 (public service), 19 (one shift industry) and 32 (Inka Ltd.).*

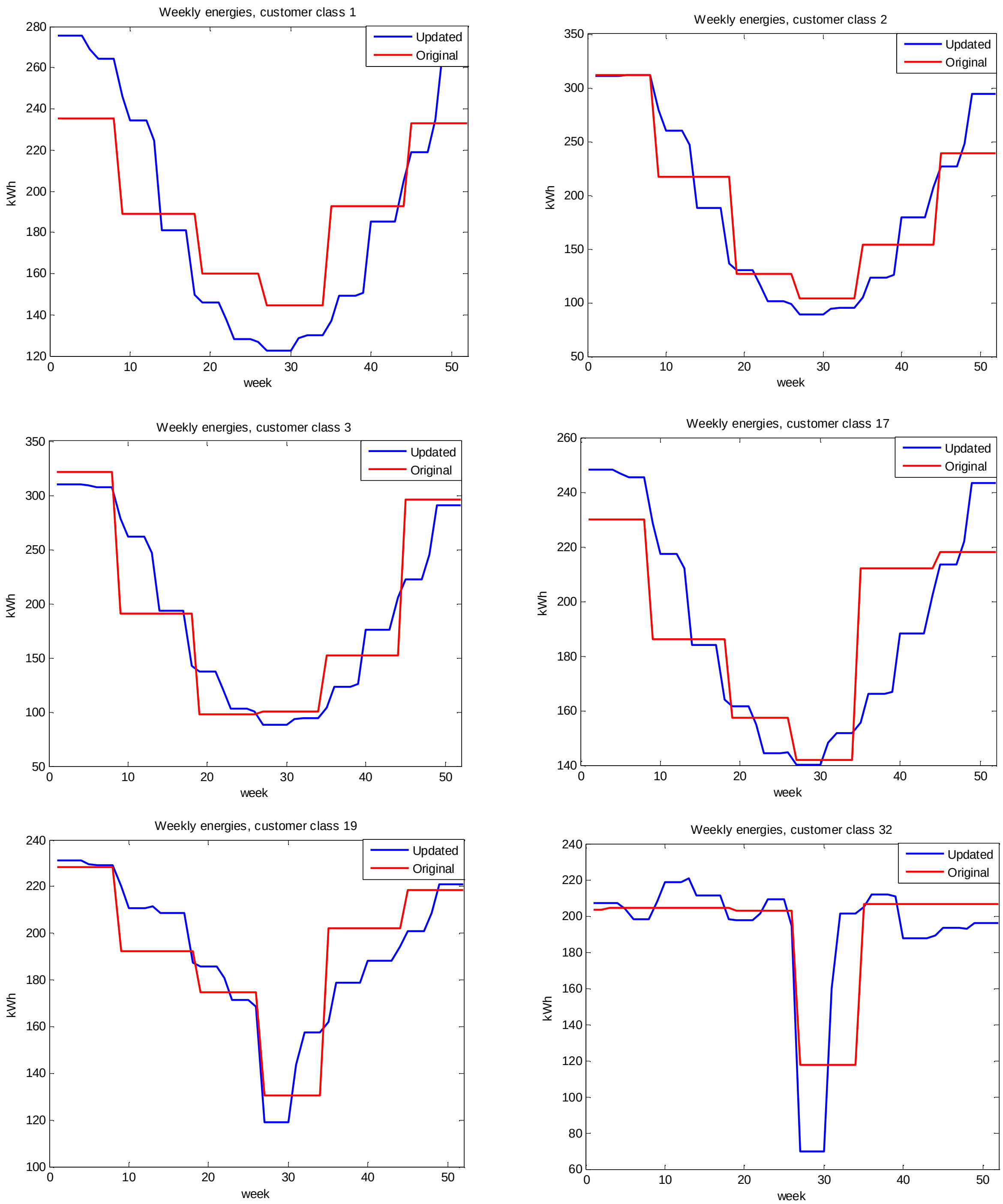

Figure 4. *Weekly energies for the original and updated load profiles. Customer classes 1 (housing), 2 (housing + direct electric heating), 3 (housing + partial electric storage heating), 17 (public service), 19 (one shift industry) and 32 (Inka Ltd.).*

In many updated load profiles, the peak power is smaller than in original load profiles. Network calculation with mean loads may therefore give smaller peak loads than before. On the other hand, standard deviations are larger in the updated load profiles. This will increase the load when using statistical confidence coefficients. In the updated load profiles, the peak loads are on average 22 % smaller than in the original load profiles while the standard deviations are on average 40 % higher. The exact numbers are given in Table II.

Table II. *Peak powers (W) for each updated load profile (10 000 kWh yearly energy) and average standard deviations (%).*

Profile		Peak (W)			Average std. (%)	
		Original	Updated		Original	Updated
1		3377	2248		90	86
2		3118	2376		50	63
3		4343	3679		25	76
4		6162	4858		10	106
5		4289	2595		75	83
6		2687	2377		57	77
7		8486	3406		71	109
8		3894	2138		78	94
17		3327	2121		60	52
18		1986	2001		80	67
19		3828	3053		60	98
20		2268	2633		60	59
23		2826	3451		80	148
26		2250	2122		70	25
28		4032	2708		60	79
29		2643	2354		30	17
30		1705	1563		30	34
31		1372	1463		10	15
32		1710	2032		10	34
33		1944	1978		10	50
34		2785	2751		10	41
36		3196	2069		0	29
38		2103	1908		0	10

In Figure 5, the better accuracy of the updated load profiles is verified by comparing modelled and measured sum powers for each customer class. Accurate comparison between load models and measurements is difficult because outdoor temperature has a large effect on the load levels. The reference measurements have been taken from a day which has an average temperature of -7.2 °C (Monday the 7th of February 2011). This temperature is very close to the average temperature of February, so the errors caused by the load temperature dependency should be minimal. The load profiles are normalized to February's average temperature in Virrat which is -7.5 °C. Verification data was not used in load profile update, so this analysis corresponds to situation where historical AMR data is used to make next year load forecasts. Figure 5 shows that the updated load profiles are clearly better in forecasting customer class sum loads. Plots start from hour 1 (00:00–01:00).

Even the updated load profiles don't forecast the load on customer class 32 (individual load profile for a large industrial customer) very well. In this study, forecasting the behaviour of industrial customers whose electricity consumption is dependent on economic cycles was proven to be quite challenging.

Figure 6 shows comparisons made on a distribution transformer level. Again, the comparison is made for Monday the 7th of February 2011. Due to smaller sample size and higher variation the results are not as clear as in Figure 5 but some improvement over the original load profiles can be seen. Transformer peak loads were also studied. The peak loads calculated using DMS600 network calculation software can be seen in Table III. The calculated peak loads are compared with peak loads measured in February 2011. Distribution transformers 3030, 3073, 8139 and 6141 were the only transformers with 100 % measurements coverage. On these four distribution transformers, the updated load profiles gave too low peak load estimates and original load profiles gave too high peak load estimates. For more general results, further studies are needed with more distribution transformers, longer verification period and with a calculation engine that can take load temperature dependencies into account.

Table III. *Comparison of peak load estimates.*

Distribution transformer	Measured peak load (kW)	Peak load with 95 % confidence level with original load profiles (kW)	Peak load with 95 % confidence level with updated load profiles (kW)
3030	206	207	186
3073	142	168	124
6141	125	124	119
8139	57	80	56

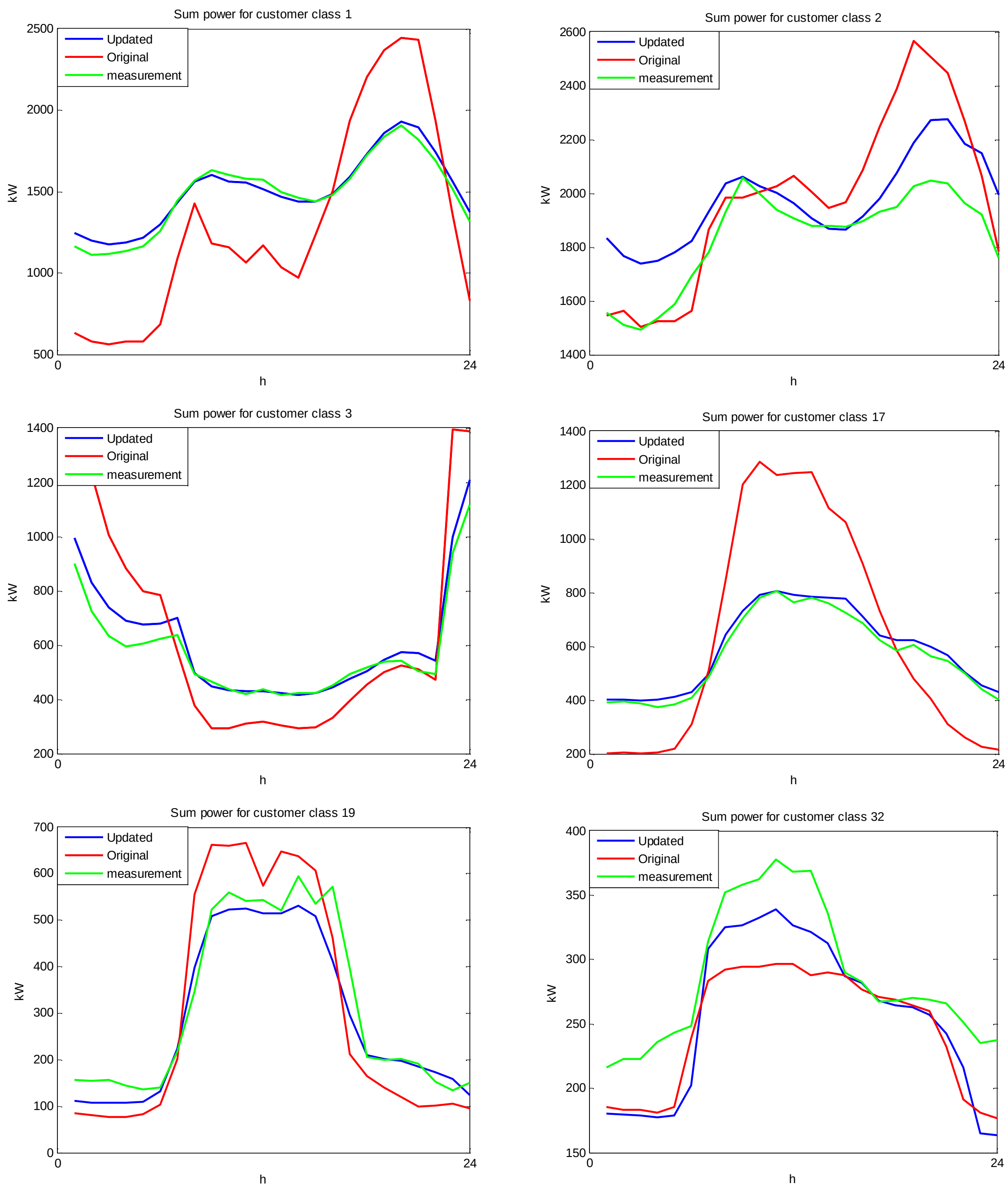

Figure 5. *Next year measurements, updated load models and original load models for customer classes 1 (housing), 2 (housing + direct electric heating), 3 (housing + partial electric storage heating), 17 (public service), 19 (one shift industry) and 32 (Inka Ltd.).*

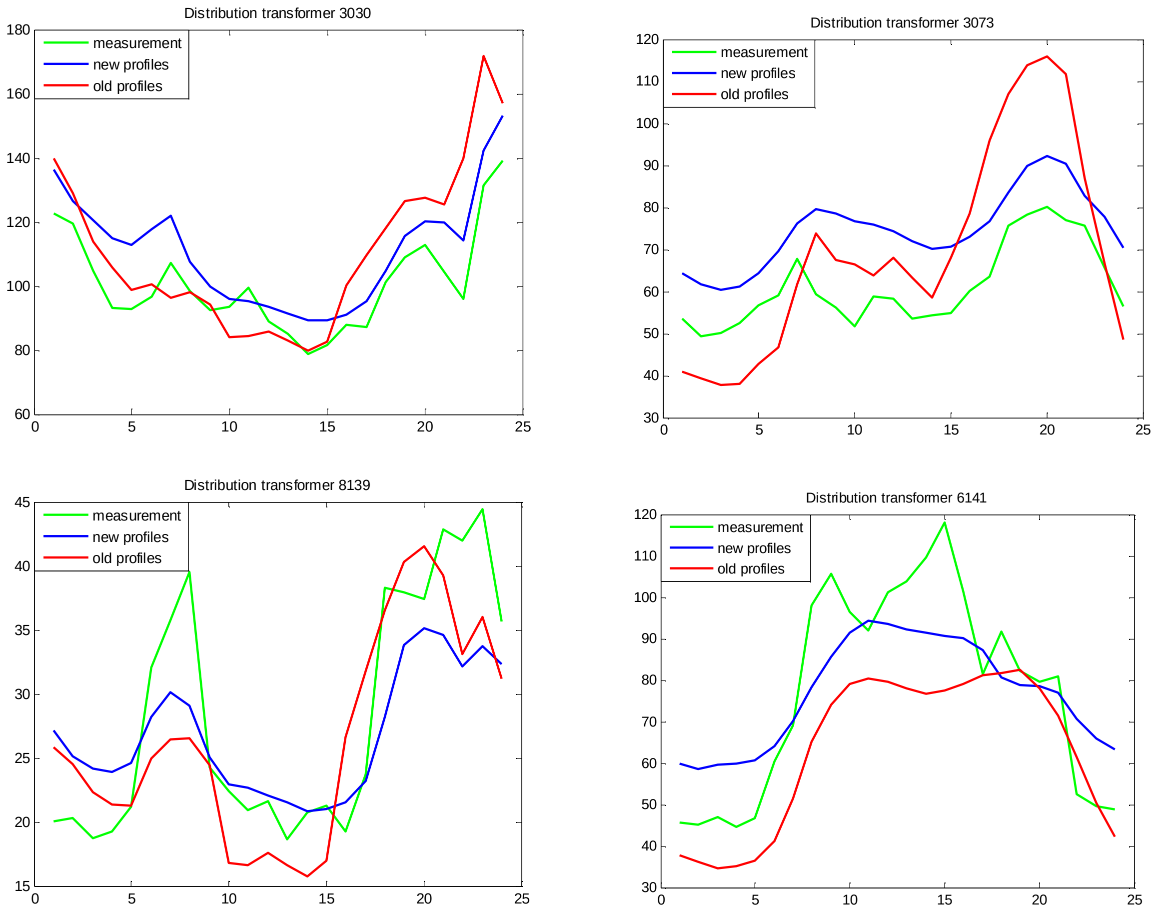

Figure 6. *Next year measurements, updated load models and original load models for distribution transformers 3030 (53 customers), 3073 (125 customers), 8139 (18 customers) and 6141 (20 customers).*

The network peak load is of great interest to the distribution network operator. Thus peak load analysis was done also on a substation level. DMS600 was used to calculate peak loads for Heinäaho substation with following results:

- According to the updated load profiles, peak load in substation Heinäaho should be between 5325–5696 kW (mean – 95 % confidence level).
- According to the original load profiles, peak load in substation Heinäaho should be between 6202–6573 kW (mean – 95 % confidence level).
- During the years 2002–2008, the measured peak hour loads in Heinäaho substation have varied between 6650 and 8760 kW.

Both updated and original load profiles underestimate the substation level peak load. This is because network calculation in DMS600 doesn't take temperature dependencies into account. On the individual customer or distribution transformer level the lack of temperature dependency modelling is partially compensated by the load variability model (standard deviation) but on substation level the relative load variability is small and thus the lack of temperature dependency modelling clearly shows.

The load profiles have been normalized to represent average load behaviour in average monthly temperature. In Virrat, the average temperature for the coldest month of the year is −7.5 °C (February) but almost every year there is at least one day with an average temperature of −25 °C.

From the load profile updating Case 1 we can conclude that the load profile updating clearly improves the average fit of load profiles but further studies are needed to determine if they have positive effect on the peak load estimates.

5 Clustering

Clustering is an analysis technique aimed to determine how the data is organized. Clustering algorithms divide a set of observations into subsets (clusters) so that the observations in the same cluster are similar in some sense. There are several clustering methods suitable for customer classification. In this study *k*-means clustering is applied for customer classification. The clustering is done based on the AMR measurements.

The k-means method is one of the most popular clustering methods used in statistical data analysis. The *k*-means algorithm assigns each point to the cluster whose centre (centroid) is the nearest. The centroid is the average of all the points in the cluster. The algorithm steps are:

1. Choose the number of clusters, *k*.
2. Randomly assign *k* points as cluster centres.
3. Assign each point to the nearest cluster centre.
4. Recompute the new cluster centres.
5. Repeat steps 3 and 4 until the assignment does not change.

In this study, customers are clustered into groups that behave similarly and customer class load profiles are calculated for each cluster. These "cluster profiles" are then used forecast electricity consumption on a following year, and results are compared to original load profiles, updated load profiles and real measured loads.

5.1 Case 1: Koillis-Satakunnan Sähkö

AMR measurements from Koillis-Satakunnan Sähkö Oy were used to cluster the customers into groups that behave similarly. 27 cluster profiles and 100 individual load profiles were formed to the 5343 measured 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 class.

The cluster profiles can't be compared directly to the original or updated load profiles since they represent different kind of customers. We can compare them only by studying how they would have forecasted the electricity consumption on the verification period for different groups of customers. Figures 7 and 8 show examples how distribution transformer level loads would have been estimated with the different load profiling methods and how they compare to the actual measured load on 3rd week of February 2011 (peak load week on the verification period). The load profiles are made to model the loads on monthly <u>average</u> temperatures, so it is clear that achieving perfect load estimates for a time period with varying temperature is impossible. Figure 9 shows the measured temperatures for the verification period and for the corresponding time period in 2010.

Figure 7 shows the estimated and measured loads on distribution transformer 3030. The load on distribution transformer 3030 has a high temperature dependency so all the load estimates during the peak load week differ significantly from the measured load. For comparison, also the previous year's measured load is shown. This also differs considerably from the verification period measurement since the temperature on previous year was different than on verification period.

Figure 8 shows estimated and measured loads on distribution transformer 3073. The load on distribution transformer 3073 has a lower temperature dependency and both updated load profiles and cluster profiles provide a good fit that is considerably better than the fit with original load profiles. Again, the previous year's measurement differs from the measurement on the verification period due to temperature differences.

The loads in figures 7 and 8 were calculated with 95 % confidence level since that is a common practice when estimating peak component loadings in distribution network calculation. From figure 7 it is clear that without temperature correction, the shape of the estimated load profiles does not correspond to the load profile during peak load situation. However, often it is enough if the magnitudes of the peak hour loads can be estimated accurately. Table IV compares distribution transformer level peak load measurements to peak load estimates done with original, updated load profiles and cluster profiles during the verification period.

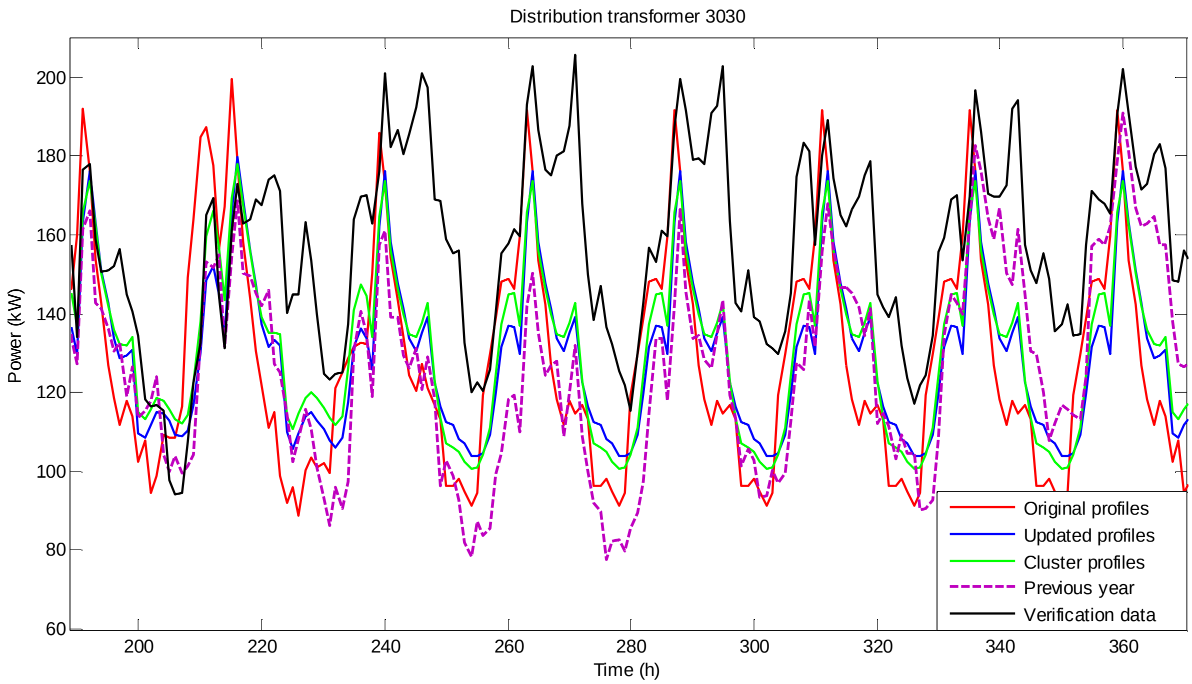

Figure 7. *Measured and estimated loads on distribution transformer 3030.*

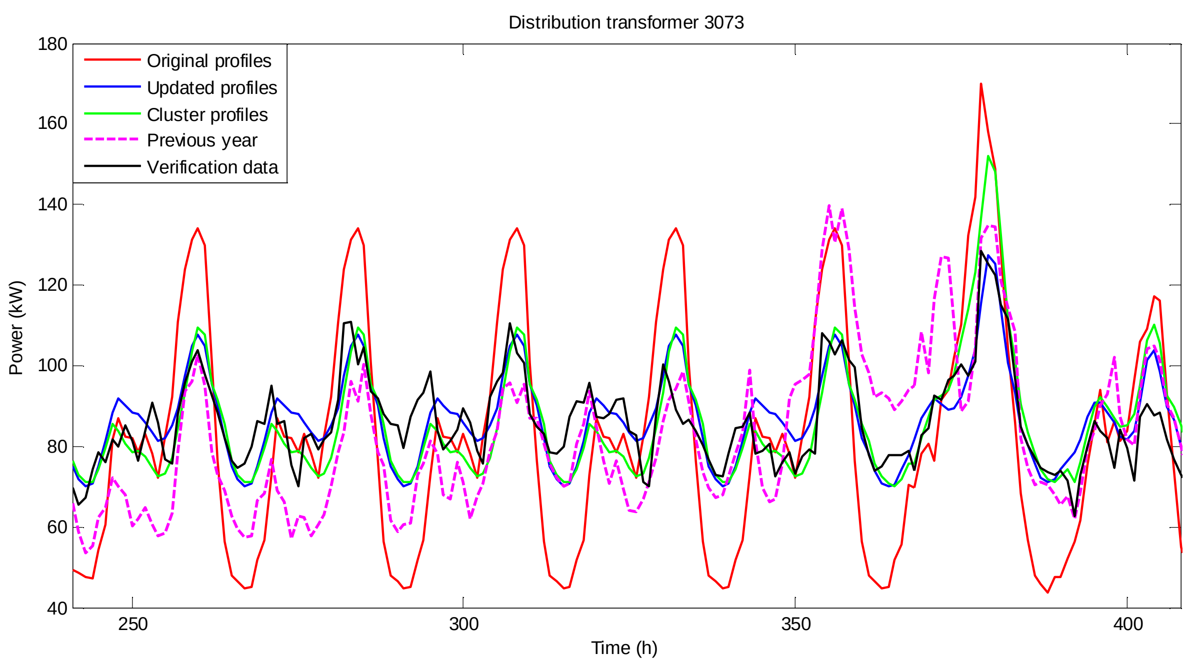

Figure 8. *Measured and estimated loads on distribution transformer 3073.*

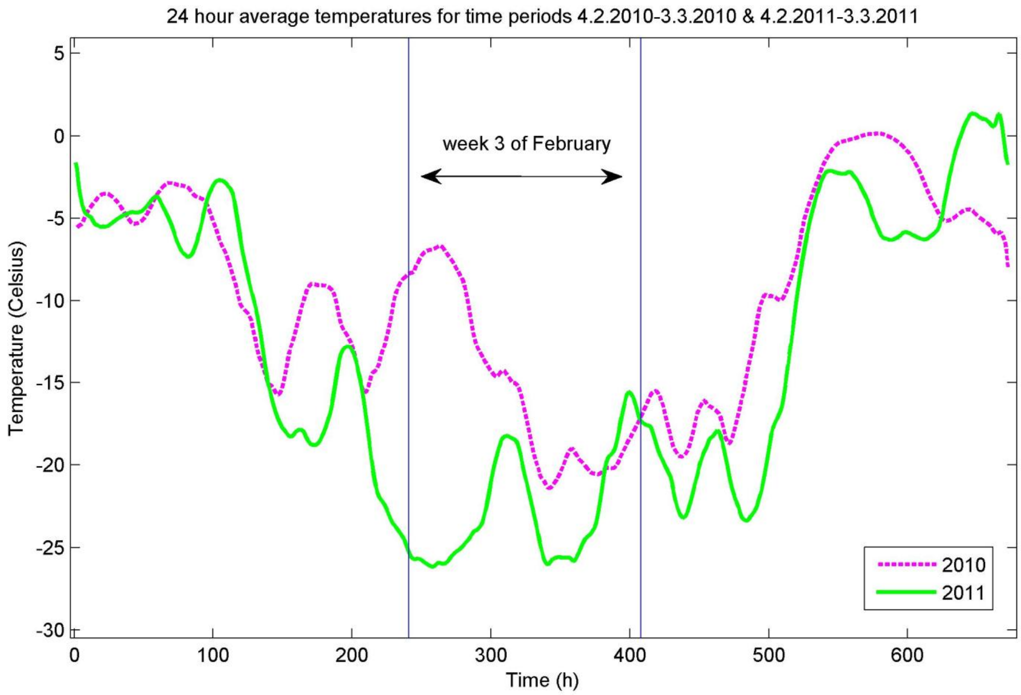

Figure 9. *24 hour average temperature for the verification period and for the corresponding time period in 2010.*

Table IV. *Comparison of transformer level peak load estimates.*

Distribution transformer	Measured peak load (kW)	Peak load with 95 % confidence level with original load profiles (kW)	Peak load with 95 % confidence level with updated load profiles (kW)	Peak load with 95 % confidence level with cluster load profiles (kW)	Peak load on previous year at the same time (kW)
3030	206	200	180	178	195
3073	142	170	127	152	140
6141	125	126	134	106	118
8139	57	68	54	57	59

From table IV we see that with 95 % confidence level the original load profiles gave too high peak load estimates and the updated load profiles and cluster profiles gave too low peak load estimates for the verification period. The low values in updated and cluster load profile peak loads can be explained with the fact that standard deviations for these profiles have been calculated from measurements that have been normalized to long term average monthly temperature. Thus the standard deviations don’t include the uncertainty caused by temperature variation but the temperature has to be taken into account separately. Table V shows the peak loads for updated load profiles and cluster profiles when -25 °C temperature is assumed (minimum temperature during the verification period was -26 °C). In this case, the 50 % confidence level gives the best estimates for the peak loads. The higher 90 % and 95 % confidence levels give too high peak load estimates. However, it is impossible to make unquestionable conclusions from a sample this small (1 month verification data, 4 distribution transformers).

Results with more statistical significance can be achieved by studying how the different load models would have estimated the peak load on a customer level. Table VI shows the estimated and measured average peak loads to all 5343 customers. On a customer level, the best peak load estimates are achieved with updated load profiles and with cluster profiles when they are calculated at the temperature of -25 °C and with the 95 % confidence level.

Table V. *Comparison of peak load estimates when -25 °C temperature is assumed.*

Distribution transformer	Peak load with 95 % confidence level with updated load profiles (kW)			Peak load with 95 % confidence level with cluster load profiles (kW)		
	50 %	90 %	95 %	50 %	90 %	95 %
3030	212	231	235	215	231	235
3073	139	155	159	157	176	182
6141	114	144	153	108	115	118
8139	50	61	65	58	66	69

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

Method	Average peak load (kW) with 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 at -25 °C	4.1	6.4	7.1
Cluster profiles	3.8	5.8	6.4
Cluster profiles at -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		

Good peak load estimates were also achieved by using the previous year's peak loads as estimates for the peak loads on the verification period. This confirms that it would be possible to use previous year's AMR measurements in a distribution network follow-up calculation where the purpose is to determine the network maximum loadings or minimum voltages. However, the raw AMR measurements should be used only in calculations where the peak (or minimum) loads of the year are estimated. The load profiles are still needed in calculations where the effects of temperature or random variations of the loads must also be taken into account.

In this study, the updated load profiles and cluster profiles were calculated from one to three years of AMR measurements, depending on the measurement availability. Usually longer measurement period means better load profiles [8], but sometimes the customer's electricity consumption profile changes abruptly and the pre-change measurements should be forgotten. On residential customers, these changes can be caused for example by change in the heating solution, an addition of new devices, such as air conditioning or the change of customer activity e.g. from agriculture to pure housing. On industrial customers, these sudden changes can be caused by economic cycles, expansion or reduction of production or changes in working cycle.

Figure 10 shows February's average energy consumption during the years 2008–2011 on a certain commercial customer. After the year 2008, the consumption profile has changed notably. The level of consumption has risen, and above all, the consumption on Saturday has increased significantly. In order to improve the load profiling accuracy, this kind of changes should be detected automatically.

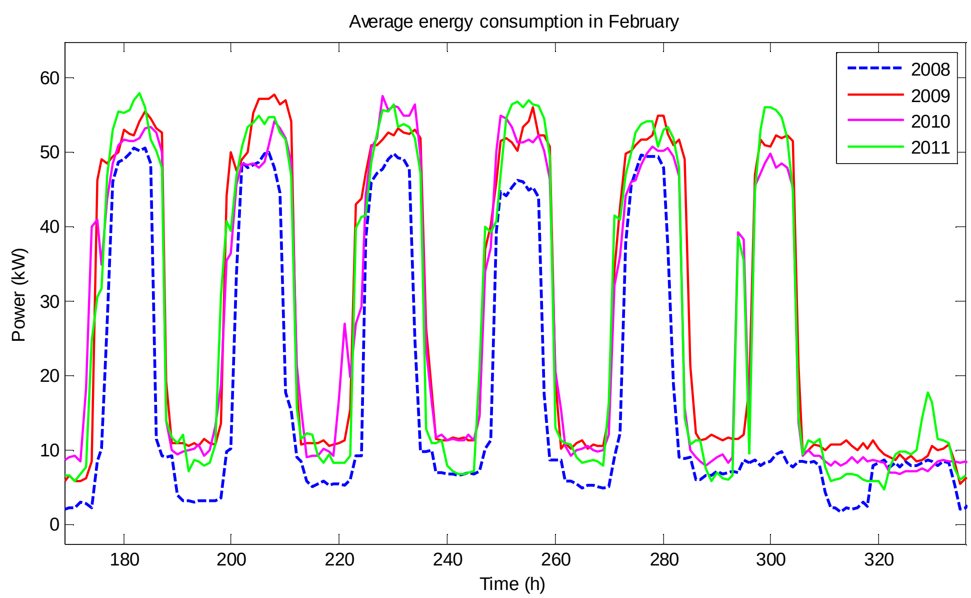

Figure 10. *Example of a customer who's electricity consumption profile has changed.*

From the clustering Case 1 we can conclude that making accurate load estimates is difficult even with updated load profiles or with cluster profiles if no temperature information exist. When forecasting next year’s peak loads, we must take the expected minimum temperatures into account. Last year’s measurements usually provide a good indication for future peak loads since almost every year there is at least one cold spell, only the timing of this spell is unknown beforehand. In this Case, good estimates for the customer level peak loads were achieved when the updated load profiles and cluster profiles were scaled to the temperature of −25 °C and 95 % confidence level was used. For the distribution transformer level loads the best confidence level was 50 % but this still needs further verification since the sample size was too small.

6 Lessons learned and future work

In this study, we showed that the load profile updating and clustering can both increase the load profiling accuracy. The applied clustering method minimized the Euclidian distances between pattern vectors, thus the average fit of the cluster profiles was very good. Verifying improvements in peak load estimates was surprisingly difficult. Cluster profiles provided good peak load estimated for individual customers, but the verification on distribution transformer level suffered from small sample size. Further studies are needed to confirm the results. If the results are not good enough, then we could give the peak load hours a bigger weight in the clustering, as was done in [9].

The load profiling method used in this study separated random load variations and load variations caused by outdoor temperature changes. Thereby, the peak load estimation required the use of both confidence intervals and temperature scaling. The peak load magnitudes depend on the confidence level and expected minimum temperature. Further studies are still needed for determining the recommended confidence levels and minimum temperatures for peak load calculation.

If there is a sudden change in the customer’s electricity consumption pattern, we should detect that and use only the latest measurement data that reflects the customer’s current consumption habits. Method for detecting these changes should be studied.

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