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Analysis and prediction of electricity consumption using smart meter data

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***Abstract*— This paper is considering application of smart meter data to predict electricity consumption of household consumers. The availability and amount of data is suitable for in-depth statistical analysis of electricity consumption profiles and the study of consumer's behavior. Prediction of electricity consumption is very important for electricity traders to balance their electricity purchase and sales portfolio, as well as to prepare optimal price products (offers) for their clients. Electricity consumption data of 500 consumers divided into 6 consumers groups was analyzed. The consumption data was derived from smart meters. As the next step, modern methods of electricity consumption forecasts would be applied to predict household electricity consumption.**

Keywords — smart meters, electricity consumption profiles, statistical analysis, load aggregators.

I. INTRODUCTION

Nowadays for electricity traders and load aggregators it becomes very important to learn the behavior and consumption profiles of their clients. Using these data electricity suppliers could be better prepared to meet the demand of electricity consumers.

Smart technological solutions allow not only to obtain electricity consumption profiles, but also to manage electricity consumer's decisions and demand response.

TABLE I. CONSUMER GROUPS PARTICIPATED IN THE PROJECT

Group	Electricity consumptions, kWh	Number of participants
Group Nr. 1	0 – 200	35
Group Nr. 2	201 – 300	66
Group Nr. 3	301 – 450	93
Group Nr. 4	450 – 650	55
Group Nr. 5	651 – 1000	31
Group Nr. 6	From 1001	219

The Pilot Project aimed in promotion of energy efficiency in households was implemented by Latvian power utility Latvenergo in 2013 by installation of smart meters to 500 households, selected and segmented in 6 groups by average monthly electrical energy consumption (table 1).

To implement the Pilot Project the following infrastructure was created (Fig. 1). Power line communication (PLC), Global System for Mobile communications (GSM) and General Packet Radio Service (GPRS) communications are being used for meter reading. 38 PLC and 462 GPRS meters were installed. Open type Meter Data Collection System (MDCS) are being used for meter data collection and export to the web portal and Billing System.

35 households were provided with in-home display kits enabling the Home Area Network (HAN) for more detailed appliance consumption data and switching control possibilities for individual appliances.

Clients provided with electrical energy consumption data in Latvenergo Customer portal www.e-latvenergo.lv. The Portal provides clients with detailed information about their load profile with time interval of every 5 minutes. It is also possible to observe energy consumption, electric load and CO_2 emission data for different time periods. With the Pilot Project the smart phone application for displaying energy consumption data from the Customer portal was developed.

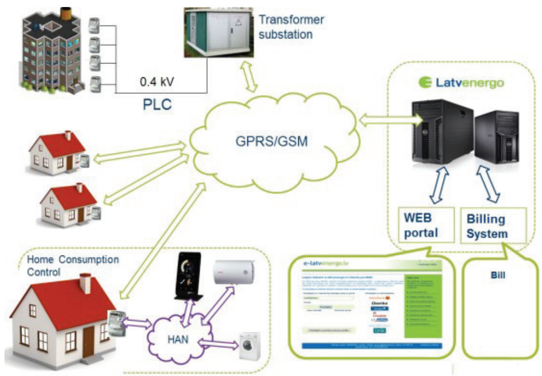
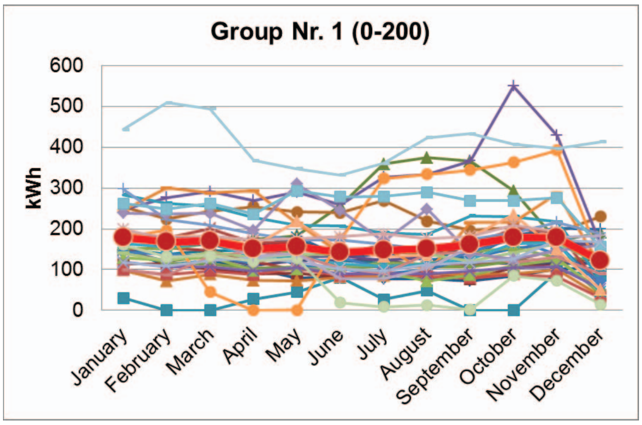


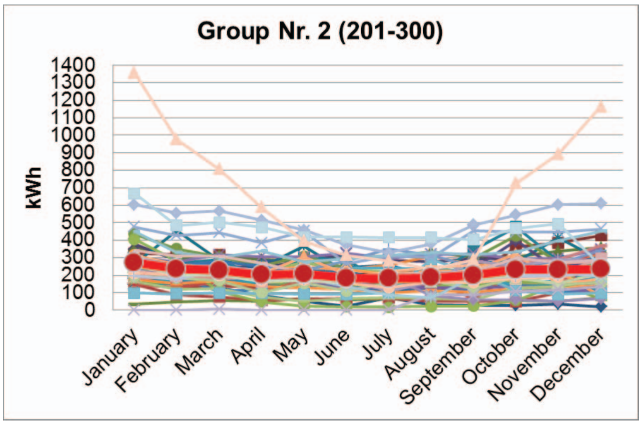
Fig. 1. Smart grid infrastructure within the Latvenergo Pilot Project

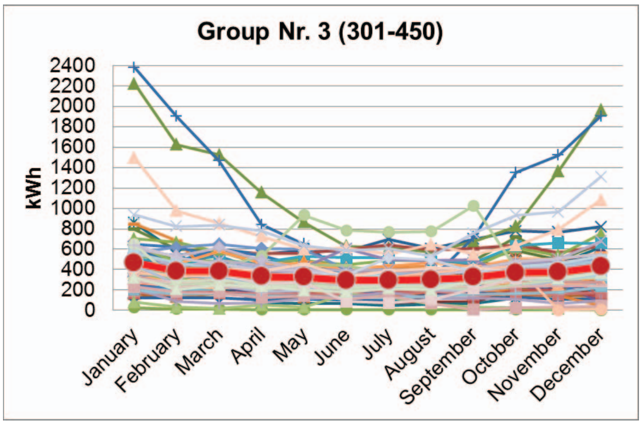
II. Analysis of Monthly Data

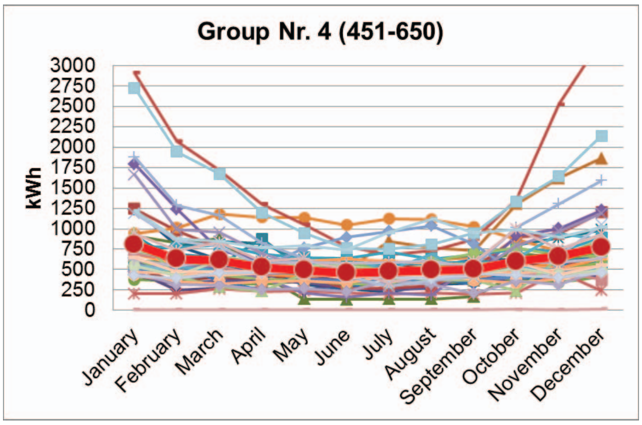
Using smart meters electricity consumption data was measured and transmitted to Latvenergo Customer portal. During this research we had a possibility to access the data from all the 500 smart meters for the period from the 1st of May 2013 to 31st December 2014. Hourly data arrays were analyzed in this research [7]. For the considered period the amount of accumulated data was significant: 500 customers x 610 days x 24 hours = **7 320 000 data points**.

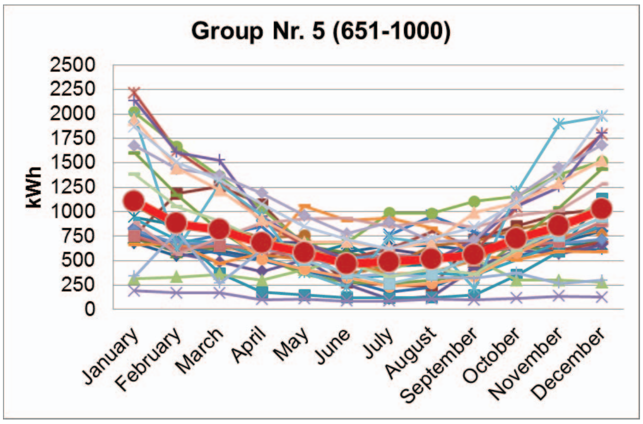
For the evaluation of measured data methods of statistical analysis were applied. First, monthly electricity consumption data (Fig. 2) was analyzed to select representative consumers for each of the consumer groups.











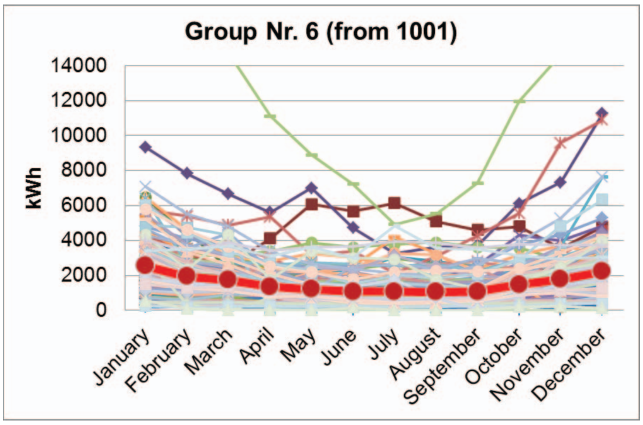


Fig. 2. Analysis of monthly electricity consumption for different consumer groups.

Profiles of electricity consumption (fig.3) are used by load aggregators to prepare optimal price products (offers) for their clients. Combining electricity consumption patterns and electricity price forecasts, they determine optimal electricity sales price, which would be profitable for the customer and risk free for the trader.

Electricity consumption profiles are also important to balance electricity purchase and sales portfolio of electricity traders. An error in electricity consumption forecasting is too expensive for the trader, deduction balancing costs from his profits.

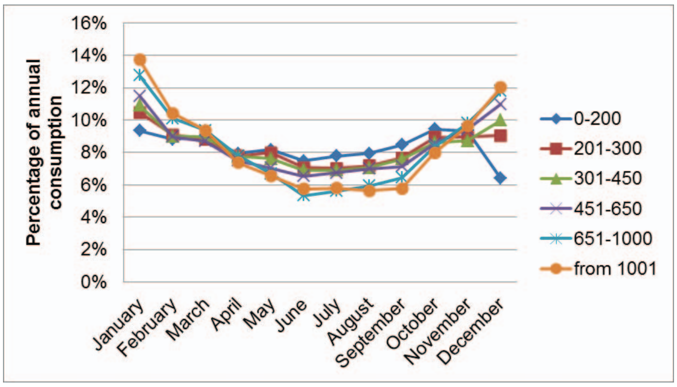
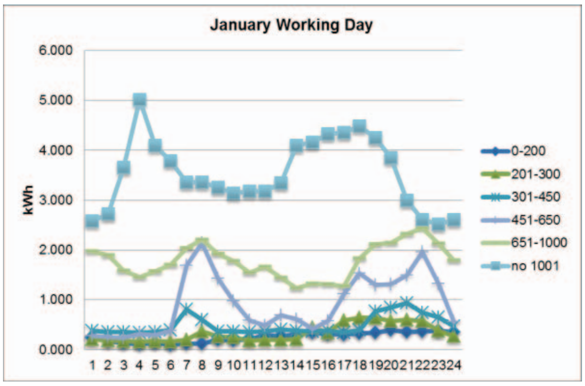
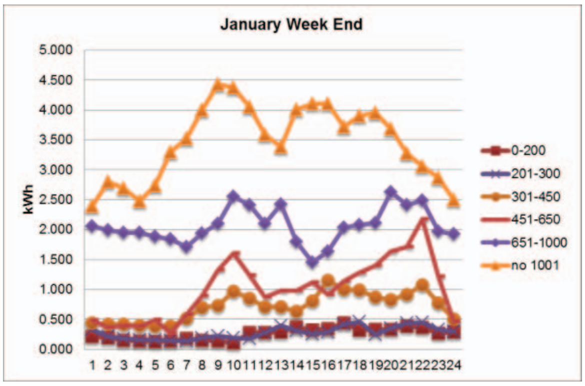


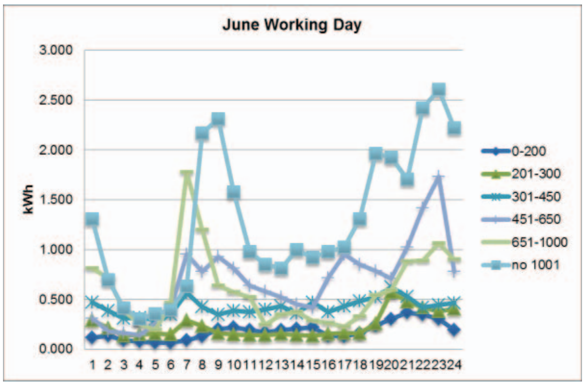
Fig. 3. Analysis of monthly electricity consumption for different consumer groups.

III. Analysis of Hourly Data

For analysis of hourly consumption a large array of data was analyzed. For the selected representative customers, hourly electricity consumption of the average working and week-end day of every month of the year were determined (fig. 4).







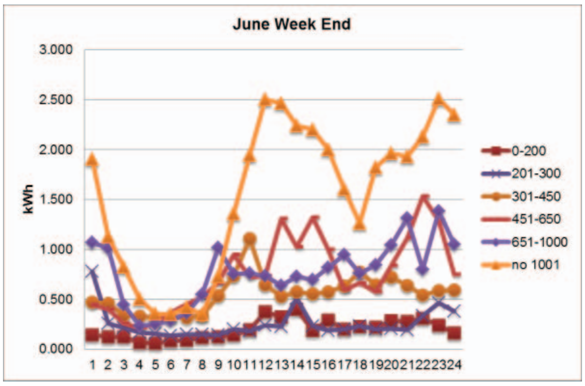


Fig. 4. Analysis of hourly electricity consumption

IV. Statistical Analysis of Loads

To make predictions of daily electrical loads, it is necessary to analyze a historical data and determine the factors, which cause the load to change. Taken into account, that load is a random variable, a probability theory and statistical methods shall be used for this analysis.

Different methods for prediction of electricity consumption were proposed by various authors [1], [2], [3], [4], [5].

Integral and differential characteristics are used to explore the irregularity of daily load curves [6]. To calculate integral parameters of daily load curve, hourly load values for the whole 24 hour period are used, but for evaluation of differential characteristics only extreme points of a load curve are needed, as indicated in the Fig. 5.

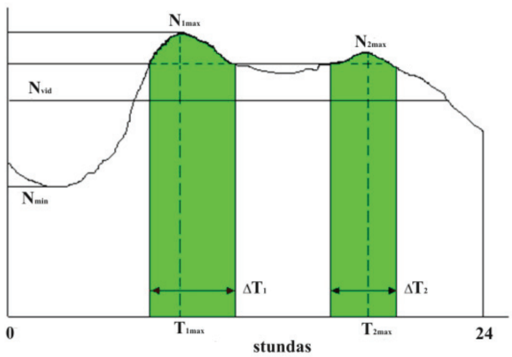


Fig. 5. Electric load and parameters

The following parameters: load curve shape factor k_f, root mean square deviation $\sigma(N)$ from the average daily value and duration of energy consumption $\Delta t_{\max}^{(\Sigma)}$ at the period close to peak load, could be attributed to integral characteristics [6].

The parameter k_f could be calculated using equation (1):

$$k_f = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} N_i^2}}{\frac{1}{n}\sum_{i=1}^{n} N_i} = \frac{\sum N_{rm}}{N_{avg}} \qquad (1)$$

where N_i – hourly load value of i-th point of daily load curve;

n – number of points at daily load curve;

N_{rm} – root mean square load;

N_{avg} – average daily load (the mathematical expectation).

The parameter k_f, which is calculated using equation (1) is fundamentally flawed. For load curves with no distinct differences between the minimum and maximum loads, the value of k_f differs from 1 only in the third or fourth sign, that is why it is better to use the modified parameter k_f^*:

$$k_f^* = 100(k_f - 1) \qquad (2)$$

Root mean square deviation $\sigma(N)$ is determined using widely known formula from the statistical theory:

$$\sigma(N) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(N_i - N_{avg})^2} \qquad (3)$$

This parameter is expressed in units of power, but its numerical value is directly proportional to the width of the range in which load values are changing for 24 period.

The parameter $\Delta t_{\max}^{(\Sigma)}$ is the aggregate time, when electricity consumption exceeds a given threshold (it corresponds to the shaded by green color part of the Fig.5). This threshold is usually specified as part of the peak load. In the example given on Fig.5 $N_p = N_{1\max}$. The expression for the calculation of this indicator is the following:

$$\Delta t_{\max}^{(\Sigma)} = \sum_j \Delta t_j \mid N_j \geq (1-\alpha) N_p \qquad (4)$$

where j – value of time slice, where the load exceeds the set threshold equal to $(1-\alpha)N_p$, $\alpha < 1$ - level of load reduction in comparison with peak load.

The following parameters: maximum $k_{\max}$ and minimum $k_{\min}$ load curve coefficients, λ - ratio of $k_{\max}$ and $k_{\min}$, relative width k_d of the variable part of load curve, as well as morning and evening peak ratio k_r could be attributed to differential characteristics [6].

There could be several maximum and minimum extreme points on the daily load curve. The highest possible extreme point corresponds to the daily peak load N_p:

$$N_P = \max\{N_{\max}^{(i)}\}, \qquad i = 1,2,..., n \qquad (5)$$

The lowest possible extreme point corresponds to the absolute minimum load $N_{\min}$ of the day. Maximum and minimum load curve coefficients could be determined as ratios:

$$k_{\max} = \frac{N_p}{N_{vid}}, \qquad k_{\max} \geq 1 \qquad (6)$$

$$k_{\min} = \frac{N_{\min}}{N_{avg}}, \qquad k_{\min} \leq 1 \qquad (7)$$

$$\lambda = \frac{N_p}{N_{avg}} = \frac{k_{\max}}{k_{\min}} \qquad (8)$$

The daily load fluctuations in the relative form could be calculated, using the following equation:

$$k_d = \frac{\Delta N}{N_{avg}} = \frac{N_p - N_{\min}}{N_{avg}} = k_{\max} - k_{\min} \qquad (9)$$

If the load curve becomes absolutely smooth ($N_1 = N_2,..., = N_n$), the value of $k_{\max}$ and $k_{\min}$ ratios is equal to 1 (one), while k_d ratio value – equal to 0 (zero).

There are two load peaks on the load curve of Latvian power system: the morning peak $N_{1\max}$ and the evening peak $N_{2\max}$. Accordingly, time slots $T_{1\max}$ and $T_{2\max}$ conforms to these peaks. In order to compare morning and evening peaks in a load curve, one could use a peak ratio k_r, which is given in the following form:

$$k_r = \frac{N_{1\max} - N_{2\max}}{N_{1\max}} \qquad (10)$$

Geometric interpretation of considered differential characteristics becomes clear when observing the load curve in the Fig. 5. All the values in the Fig. 5, except $T_{1\max}$ and $T_{2\max}$ shall be calculated, so considered as secondary values. They are obtained, based on daily load measurement data from smart meters.

Based on the methodology described above, electricity consumption data from smart meters for different consumer groups was analyzed. The summary of results of statistical analysis for working days of four different seasons / months (February, April, July and October of 2014) and six consumer groups is presented in the table 2.

TABLE II. CALCULATED STATISTICAL CHARACTERISTICS OF ELECTRICITY CONSUMPTION FOR WORKING DAYS

	N_{max}	N_{min}	N_{avg}	σ(N)	k_f	k_{max}	k_{min}	λ	k_d	k_r
	February									
0-200	0.397	0.103	0.245	0.082	5.438	1.616	0.418	3.866	1.198	-0.365
201-300	0.662	0.170	0.351	0.159	9.795	1.886	0.484	3.897	1.402	-0.776
301-450	1.000	0.369	0.506	0.185	6.468	1.977	0.729	2.712	1.248	-0.076
451-650	2.159	0.210	0.919	0.595	19.14	2.348	0.228	10.28	2.120	0.004
651-1000	2.077	0.928	1.466	0.293	1.973	1.417	0.633	2.239	0.784	0.156
> 1001	4.208	1.228	2.500	0.844	5.547	1.683	0.491	3.427	1.192	0.121
	April									
0-200	0.371	0.092	0.216	0.082	6.901	1.714	0.424	4.042	1.290	-0.524
201-300	0.596	0.143	0.311	0.144	10.26	1.916	0.460	4.169	1.457	-1.223
301-450	0.648	0.302	0.429	0.107	3.068	1.510	0.704	2.146	0.806	-0.028
451-650	1.930	0.184	0.776	0.513	19.91	2.489	0.237	10.50	2.252	-0.095
651-1000	1.612	0.335	0.877	0.355	7.883	1.839	0.382	4.814	1.457	0.156
> 1001	3.642	0.816	1.850	0.835	9.711	1.968	0.441	4.464	1.527	0.118
	July									
0-200	0.343	0.081	0.160	0.071	9.346	2.144	0.506	4.233	1.638	-0.212
201-300	0.563	0.154	0.270	0.130	10.89	2.080	0.570	3.647	1.510	-0.652
301-450	0.719	0.315	0.461	0.138	4.367	1.560	0.683	2.284	0.877	-0.057
451-650	1.979	0.148	0.731	0.413	14.88	2.708	0.202	13.40	2.506	-0.718
651-1000	0.908	0.139	0.427	0.201	10.55	2.127	0.325	6.542	1.802	0.162
> 1001	2.203	0.303	1.195	0.537	9.621	1.844	0.253	7.280	1.590	-0.265
	October									
0-200	0.527	0.049	0.256	0.134	12.90	2.057	0.193	10.68	1.865	-0.319
201-300	0.848	0.178	0.343	0.197	15.37	2.471	0.519	4.756	1.951	-0.703
301-450	0.803	0.277	0.388	0.144	6.656	2.071	0.714	2.902	1.358	0.148
451-650	1.740	0.176	0.740	0.449	16.96	2.350	0.238	9.892	2.113	0.142
651-1000	1.224	0.429	0.748	0.255	5.659	1.635	0.573	2.853	1.062	0.052
> 1001	3.926	1.092	2.303	0.879	7.041	1.705	0.474	3.594	1.231	0.058

Similar results of statistical analysis for the weekend days are presented in the table 3.

TABLE III. CALCULATED STATISTICAL CHARACTERISTICS OF ELECTRICITY CONSUMPTION FOR WEEKEND DAYS

	N_{max}	N_{min}	N_{avg}	σ(N)	k_f	k_{max}	k_{min}	λ	k_d	k_r
	February									
0-200	0.404	0.084	0.240	0.101	8.414	1.682	0.351	4.793	1.331	-0.764
201-300	0.633	0.152	0.309	0.129	8.395	2.049	0.492	4.169	1.558	-1.251
301-450	1.181	0.350	0.725	0.246	5.578	1.628	0.483	3.373	1.145	-0.235
451-650	2.093	0.297	1.046	0.514	11.42	2.001	0.283	7.058	1.717	0.043
651-1000	2.510	1.211	1.806	0.337	1.721	1.389	0.670	2.073	0.719	0.099
> 1001	4.023	1.506	2.905	0.890	4.585	1.385	0.518	2.671	0.866	0.005
	April									
0-200	0.429	0.084	0.214	0.095	9.387	2.004	0.392	5.111	1.612	-0.745
201-300	0.476	0.128	0.225	0.082	6.433	2.113	0.568	3.721	1.545	-1.055
301-450	0.980	0.269	0.598	0.232	7.276	1.639	0.450	3.644	1.189	0.186
451-650	1.655	0.165	0.816	0.433	13.20	2.028	0.202	10.03	1.826	-0.212
651-1000	1.878	0.665	1.179	0.290	2.972	1.592	0.564	2.822	1.028	0.232
> 1001	3.153	0.789	2.056	0.803	7.350	1.533	0.384	3.998	1.150	0.006
	July									
0-200	0.352	0.066	0.175	0.081	10.27	2.015	0.378	5.328	1.637	-0.684
201-300	0.823	0.143	0.345	0.203	16.07	2.385	0.415	5.748	1.970	-1.415
301-450	0.781	0.299	0.489	0.122	3.089	1.598	0.613	2.610	0.986	-0.121
451-650	1.309	0.140	0.669	0.353	13.07	1.956	0.209	9.379	1.747	-0.560
651-1000	0.862	0.155	0.518	0.197	6.988	1.663	0.299	5.561	1.364	-0.181
> 1001	2.591	0.338	1.390	0.615	9.354	1.864	0.243	7.663	1.621	-0.331
	October									
0-200	0.660	0.048	0.269	0.165	17.32	2.451	0.179	13.73	2.272	-0.108
201-300	0.825	0.167	0.398	0.185	10.29	2.072	0.419	4.949	1.653	-0.901
301-450	0.980	0.293	0.559	0.206	6.575	1.751	0.524	3.344	1.228	-0.050
451-650	1.751	0.176	0.885	0.535	16.83	1.978	0.198	9.975	1.780	0.066
651-1000	1.596	0.569	1.009	0.299	4.295	1.582	0.564	2.804	1.018	-0.330
> 1001	4.414	1.315	2.708	0.950	5.980	1.630	0.485	3.357	1.144	-0.264

V. USE OF ELECTRICITY CONSUMPTION PROFILES TO DEVELOP OPTIMAL PRICE PRODUCTS FOR HOUSEHOLDS

With the opening of electricity markets for households, electricity traders are looking for optimal price products for different consumer groups within this market segment. Obviously it becomes very important to understand the customer behaviour and its consumption profile to be able to offer an optimal price product.

In this research we compare different price products for the household client, equipped with the smart meter for hourly consumption measurements. Average monthly consumption of this client is above 200 kWh, so it is classified to the consumption group No. 2. Hourly electricity consumption data from the client's smart meter in 2015 are provided in the Fig. 6.

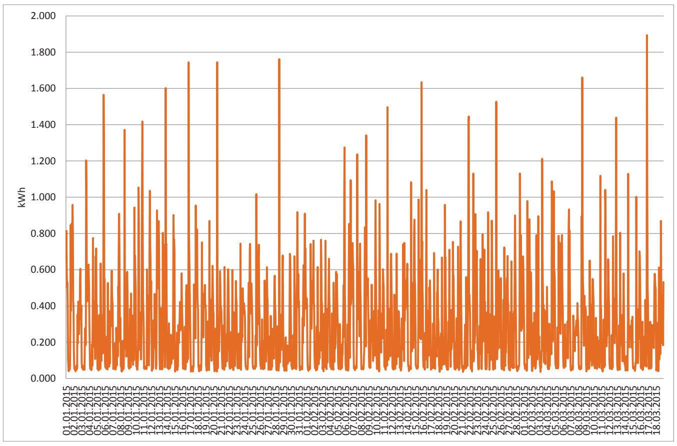


Fig. 6. Electricity consumption profile of the household client in 2015

When comparing electricity SPOT prices in the Latvian price area of Nord Pool power exchange with the price products of AS Latvenergo (traded under the brand name "ELECTRUM"), one could see, that at the beginning of 2015 electricity prices in the power exchange were lower, that fixed price products of Latvenergo (Fig. 7). That is why those household clients with smart meters, who have selected the ELECTRUM DINAMISKAIS (DYNAMIC) price product with variable hourly electricity prices, got additional profits, because of lower electricity prices in the market.

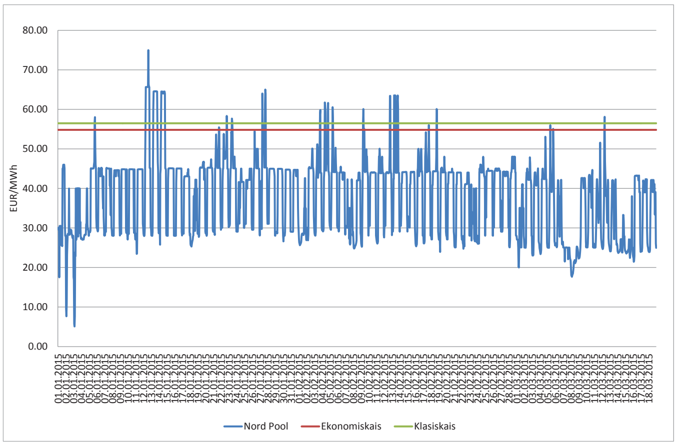


Fig. 7. Electricity prices in Nord Pool power exchange versus Latvenergo price products (in the beginning of 2015)

In comparison with fixed price products ELECTRUM KLASISKAIS and ELECTRUM EKONOMISKAIS, variable price product ELECTRUM DINAMISKAIS was more beneficial for the client in the beginning of 2015 (Fig. 8). Average daily margin for this client, comparing DINAMISKAIS and EKONOMISKAIS was about 8%, while maximum margin was 20%.

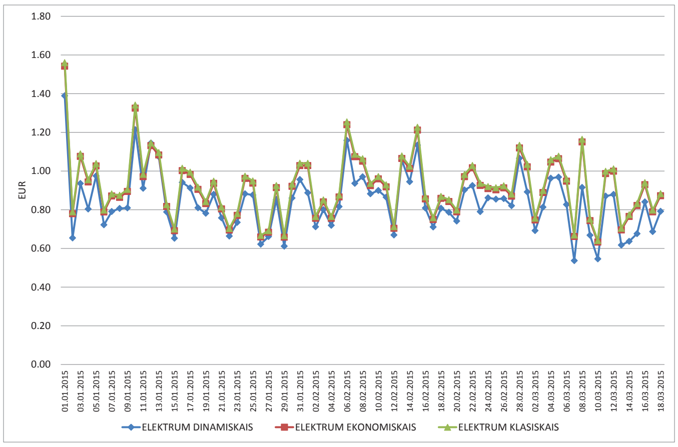


Fig. 8. Daily expenses of household electricity consumer with different price products

VI. CONCLUSIONS

This research justifies the feasibility of usage of smart meter data for prediction of electricity consumption of household consumers.

Consumption profiles of electricity consumers varies greatly by consumer group, working and weekend day, as well as seasonally. This variation is proved by the results of statistical analysis, which illustrates this stochastic nature of electricity consumption. Statistical characteristics provide numerical estimation of load variation.

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