The use of regression analysis of time series for forecasting electricity consumption of consumers and the proposal of an algorithm for calculating the electricity price

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***Abstract*—**The liberalized electricity markets, power exchanges and new metering systems create a new environment where electricity sellers could offer new opportunities for electricity consumers. With utilization of smart-grids and smarter consumers there ought to be higher expectations. For example, a new pricing system could be developed that takes actual electricity production costs into account at the exact time they are done. If smarter consumers could participate in management of electricity grid, higher demand response would develop and this would help to smooth the load curve. Smoother load curve would consequently lead to reduction of overall costs of the system.

The aim of this article was to first analyse dependence of load of a small group of residences in Estonia on temperature and to show how it is possible to forecast electricity consumption one day ahead with a simple regression analysis of time series method; secondly, to show how to correct the day-ahead forecast error when forecasting two hours ahead and to evaluate the accuracy of regression analysis of time series method; and thirdly, to propose an algorithm for calculating real-time price packages based on current market/power exchange rules.

The results of this study show that regardless of a very large stochastic component, a relatively accurate load forecasting is possible when using the regression analysis of time series method, and that the proposed algorithm would be a step closer to creating real-time pricing systems.

***Keywords*—**Algorithm for real-time pricing, load forecasting based on temperature, regression analysis, time series forecasting.

I. Introduction

The electricity market in Estonia was finally opened in the beginning of 2013. On the retail market, there are ten electricity sellers who shape the electricity prices for the consumers. Eesti Energia AS currently possesses the largest market share which is approximately 70%. Eesti Energia AS is the largest energy company in Estonia and all of its shares belong to Estonian government. All the retail sellers are buying electricity either directly from producers or from the power exchange Nord Pool. At Nord Pool, electricity sellers can buy the necessary amount of power from day-ahead market (Elspot) based on one-day-ahead forecasting and correct their forecasting errors in intraday market (Elbas).

Although there were some expectations that more different tariff systems would be introduced to the open electricity retail market, it unfortunately did not happen. All the retail sellers offer basically the same tariff systems as they did before only with different fixed contract periods. These tariff systems are:

1) Fixed price tariff system,
2) Tariff system based on the average power exchange price of the previous month.

Since these tariff systems do not take into account costs that are spent on electricity production at the moment of consumption, it is necessary to create a tariff system where electricity production costs are being considered. This tariff system is called real-time pricing system.

To initiate real-time pricing it would be necessary to install remotely readable electricity meters that are able to fixate electricity consumed during the desired time interval. As from 2017, there should be remotely readable meters at all Estonian consumers' supply points.

The aim of this article is to analyse the dependence of load on temperature [1], to show that using regression analysis of time series method for short-term load forecasting is accurate and that it would allow the retail sellers to offer consumers a real-time electricity tariff system, and finally to propose an algorithm by which retail sellers could offer dynamic pricing systems for consumers without any need to change current power exchange rules. In this article, we will study only short-term forecasting.

II. Forecasting Consumption

Forecasting of electricity consumption is very difficult since there are a lot of consumers, their consumption is largely random and there are different variables that affect their consumption. A lot of different methods have been proposed for forecasting consumption.

Naturally, it is necessary to estimate electricity consumption to assure efficient operation of the electricity system. In the

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system, a balance between generation and consumption needs to exist. It is not possible to produce more than is consumed.

Load forecasting can be usually divided into:

1) Short-term load forecasting, ranging from one hour to one week;
2) Medium-term forecasting, ranging from one week to one year;
3) Long-term load forecasting, ranging from one year to longer time periods.

Up until recently, forecasting consumption was necessary for utility companies, and network and system operators for planning and controlling. However, in a liberalized energy market, there are also electricity sellers competing on the retail market. Thus, buying energy from power exchange and reselling it to consumers also requires good forecasting models. Since retail sellers have a good overview and statistics of their consumers' habits, the forecasting should be easier and more accurate.

In load forecasting models, it is necessary to take the following load changes into account [2]:

1) Regular changes, like day-and-night, weekly and yearly periodicity, trend and nature of the load on national holidays;
2) Temperature dependence, which is for example quite high in case of electrical heating. In models, temperature dependence inertia, nonlinearities and time variations are taken into account;
3) Dependence on operating values, which is expressed as load voltage and frequency sensitivity;
4) Randomness, which is particularly noticeable in loads of small distribution grids. The relation of these kinds of loads' square deviation towards mathematical expectations is quite high. In case of small loads, hard slopes can also be present that are not compatible with the normal distribution;
5) Maneuverability - The load is managed mostly indirectly through electricity tariffs. However, some kind of direct control by the power grid operator can also take place. Maneuverability is basically transmission grid node load changes that are caused by switching in distribution grid.

There are many different methods that are based on regression analysis, time series, neural networks, box-jenkis models, expert system approaches and artificial neural networks (ANN) [3]. The most commonly used forecasting techniques are neural network algorithms, time series approaches, regression techniques and expert system approaches [4]. A method is chosen primarily on the basis of the character of the source data, their volume and the necessary results (forecasting time, accuracy etc.). The time series and regression techniques are the two major classes of conventional statistical algorithms, and have been applied successfully in this field for many years. The expert system based algorithm for short-term load forecasting uses a symbolic computational approach to automating intelligence. This approach takes advantage of the expert knowledge of the operator which is, however, neither easy to elicit nor articulate. A major advantage of using ANN over expert systems is its non-dependency on an expert. Furthermore, ANN also performs non-linear regression among load and weather patterns and can also be used to model the time series method or as a combination of both [5].

Difficulty in load forecasting arises due to its nonlinear and irregular variation [6], which forecasting is complicated, if not impossible.

If weather condition is taken into account in forecasting the load, then the load is given in the form of [6]:

$$l(t) = l_a(t) + l_i(t) + l_d(t) + l_n(t) \tag{1}$$

where $l_a(t)$ stands for irregular load changes in the future, $l_i(t)$ for weather independent component, $l_d(t)$ for weather dependent component, and $l_n(t)$ for noise residual or stochastic component.

Independent and stochastic component can be further divided into different components. Similarly, weather dependent component can be divided into different components depending on different weather conditions. The load may be influenced by different weather parameters such as temperature, humidity, wind speed, cloud cover and also abnormal situations such as thunderstorms, etc. [1], [5].

Nevertheless, it is important that a forecasting model is simple, accurate and convenient to use. In particular, it is necessary to make clear what is affecting the load the most and then build a forecasting model, which takes that parameter into account.

Studies have shown that the main influence in most situations is temperature [5]. Therefore, we set out to determine whether and how much the household load depends on the outside air temperature. We decided to use regression analysis for load forecasting because this is suitable for forecasting loads based on time series. So, we needed to ascertain that the proposed regression analysis of time series method is suitable and sufficiently accurate for the electricity sellers to use it for forecasting.

III. Overview and Use of the Proposed Approach of Regression Analysis

For forecasting, it is necessary to establish a mathematical model for describing the load. In general, the load can be described as a simple model:

$$l(t) = l_e(t, C, b) + \theta(t) \tag{2}$$

where $l(t)$ stands for actual load, $l_e(t, C, b)$ for mathematical load expectation, $\theta(t)$ for stochastic component, t for time, C for temperature, b for wind.

Mathematical load expectation describes regular changes in the load, for example overall growth, seasonal, intra-week, intra-day periodicity. Stochastic component describes a random load change that cannot be estimated. It is possible to reduce the proportion of the stochastic component by taking into account more variables. However, it is not possible to eliminate the stochastic component completely. Naturally, when using weather (temperature, wind, etc.) as an input in load forecasting, then the weather forecasting precision is affecting load forecasting accuracy. However, weather forecasting is not a subject of this work.

Mathematical load expectation depends on different influences that are described above. In this work, we are taking into account the three main factors that affect load:

1) Day (weekend, working day etc.),
2) Time,
3) Temperature.

In order to determine the dependence of household load on outside temperature and to test the proposed regression analysis of time series method, we analysed measurements taken in Loo village near Tallinn, Estonia during 1st of January – 31st of December 2012. Altogether, individual consumption of eleven private houses and one apartment building with 60 apartments was measured. Meteorological data were obtained from Estonian Meteorological and Hydrological Institute's meteorological station in Harku. The measurement period was 1 year long, i.e. 8784 h. After sorting out various erroneous measurements, 6497 hours of data, i.e. 74% of the data remained.

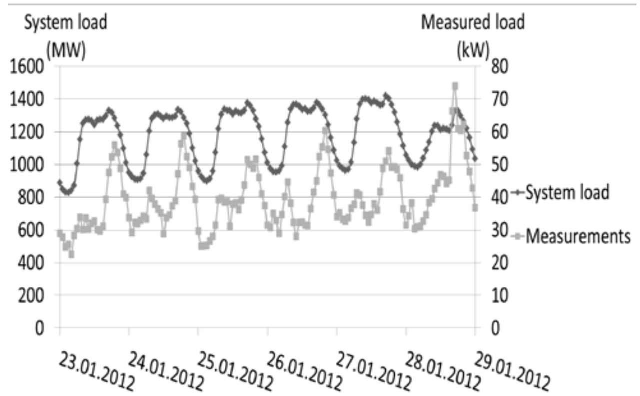

Fig. 1 Estonian whole power system load and measurements carried out in Loo village during the period January 23rd – 29th of 2012.

Fig. 1 shows a comparison of Estonian power system's whole consumption, based on Elering's measurement data, and measurements carried out in Loo village. Elering AS is an Estonian transmission system operator (TSO). The Fig. shows that, in general, the load curves are similar, however, in case of measurements carried out in Loo village, all the consumers are strongly affecting the load curve and all the unpredictable changes are also affecting the load curve. This means that in the models developed in this study, the stochastic component will likely play a large role.

In theory, forecasting should take into account temperature sensitivity and inertia, which are more sensitive in winter than during summer [2]. Inertia and temperature sensitivity are different for every customer and depend on the heating system and the construction of the building. In this work, a separate inertia, however, is not taken into account.

Fig. 2 shows customers' load dependence on temperature surveyed on weekdays at 1 p.m. Despite the fact that the weekdays are not distinguished separately, this Fig. shows a strong correlation between temperature and consumption. Fig. 3 shows customers' load dependence on temperature surveyed on the days off (weekends and holidays) at 1 p.m. Surely, it should be mentioned that when looking at private houses and apartments separately, there is practically no correlation between electricity consumption of apartments and outdoor temperature. Although the apartment building has central heating and the weather factors that affect consumption are mostly daylight hours, apartments were not excluded from this study. Thus, it can be concluded that load dependence on temperature was mainly caused by private houses.

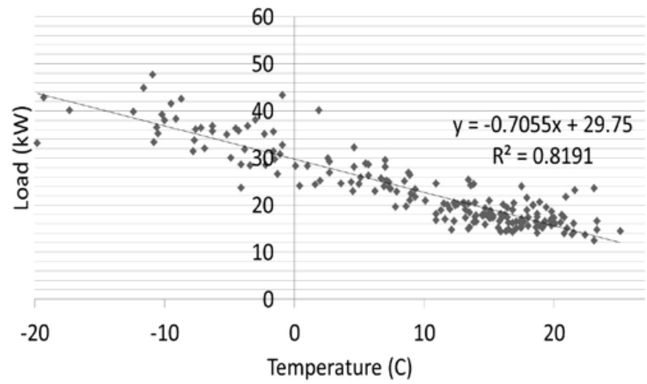

Fig. 2 correlation between load and temperature on working days at 1 p.m.

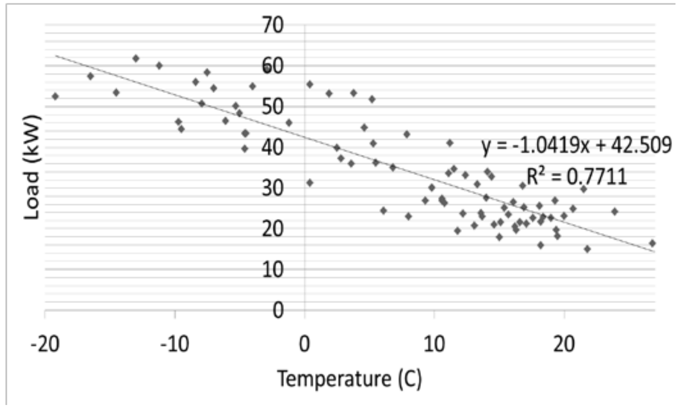

Fig. 3 correlation between load and temperature on days off at 1 p.m.

The Fig. 2 and Fig. 3 clearly show that the relationship between the measured temperature and load is negative, i.e. the increase in temperature leads to a decrease in consumption, and vice versa. The relationship may also be positive depending on the geographic location. A positive correlation for example has been observed in regions with warmer climatic conditions, where the increase in temperature leads to an increase in consumption, and vice versa [7], [8].

For Fig. 4 and Fig. 5, different working days were separated and a correlation between load and temperature on Mondays and Tuesdays at 1 p.m. was analysed. For Fig. 6 different days off were separated. The coefficient of determinant R^2 shows how a large part of the measurements is explainable with the proposed method. As shown on Fig. 4, Fig. 5 and Fig. 6, the actual loads on different days varied and the consumers had different habits on different days. The figures also show that differentiating weekdays results in a much stronger dependence between temperature and load.

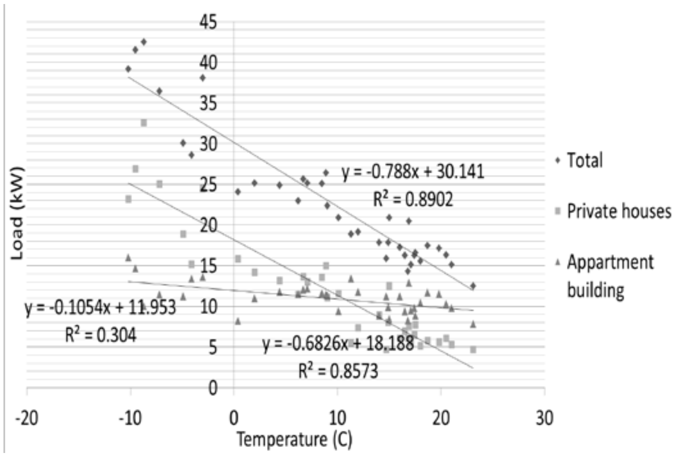

Fig. 4 correlation between load and temperature on Mondays at 1 p.m.

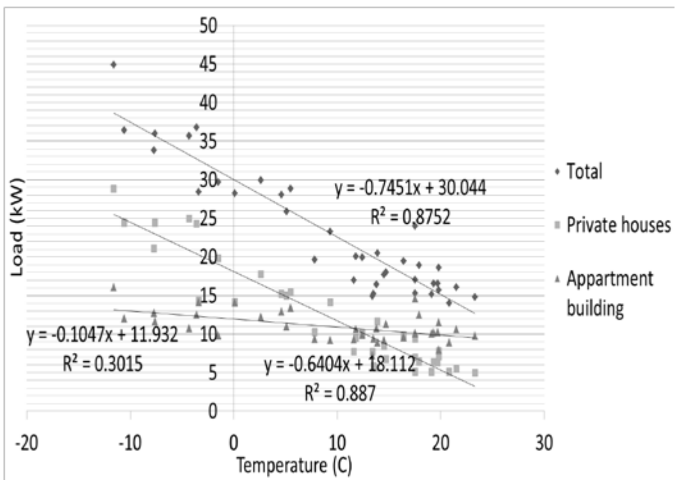

Fig. 5 correlation between load and temperature on Tuesdays at 1 p.m.

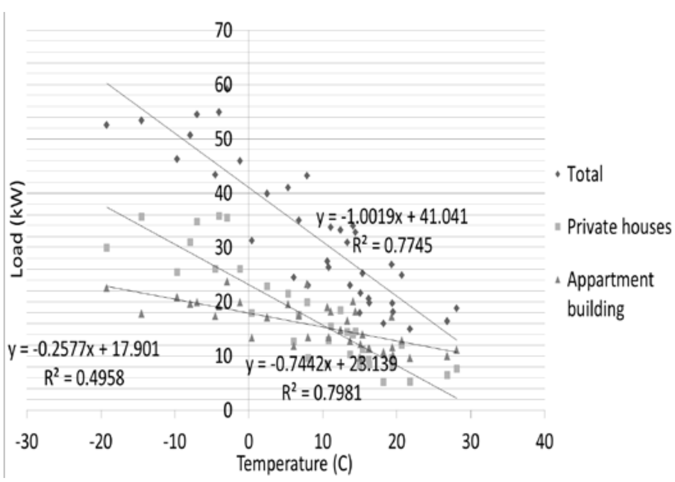

Fig. 6 correlation between load and temperature on Saturdays at 1 p.m.

To distinguish between the time of day and day of, we created a model for each day and hour on the basis of obtained measurements. In this work, we assumed that the temperature and load have a linear relationship, which depends on the time of day and day of. In addition, we calculated separate functions for holidays. Thus, for a total of 24 hours per day, 7 days a week and public holidays in separate functions, in all we created 192 functions to characterize load dependence on temperature. For the observed customers, we actually created daily load curves on the basis of time series to which we included temperature dependence. The general shape of each function can be provided as:

$$l_{Elspot}(t,d) = a(t,d) \cdot C + b(t,d) \qquad (3)$$

where $l_{Elspot}(t,d)$ stands for hourly consumption, depending on the time of day and day of (unit kWh); $a(t,d)$ and $b(t,d)$ for parameters, which depend on the time of day and day of; and C for temperature (unit ^{0}C).

Fig. 7 shows the measured and one-day-ahead forecasted loads. For load forecasting, we used actual temperatures measured in Harku's meteorological station. The Fig. 7 shows that on a large scale the predicted and the actual load curves coincide. The load is also affected by irregular changes, which cannot be forecasted in advance.

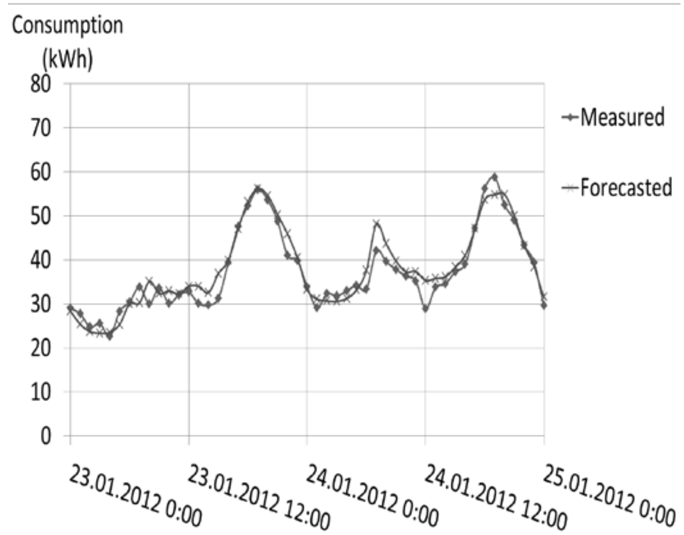

Fig. 7 measured and one-day-ahead forecasted consumption during the period of January 23rd – 24th of 2012.

IV. Correction of Regression Analysis of Time Series Method and Evaluation of Its Accuracy

Use In order to compensate the one-day-ahead forecasting error, we used the function:

$$l_{Elbast}(t+2) = l_{Elspot}(t+2) + l_{Elspot}(t+2) \cdot \cdot \frac{\sum_{t=-1}^{-4}\left[l_a(t) - l_{Elspot}(t)\cdot\alpha_t\right]}{4 \cdot l_{Elspot}(t)} \qquad (4)$$

where $l_{Elbast}(t+2)$ stands for two-hours-ahead forecast (unit kWh), $l_{Elspot}(t+2)$ for one-day-ahead forecast (unit kWh), $l_a(t)$ for actual load at time t, and α_t for coefficient that takes into account the importance of the previous hour's difference.

In order to give a higher priority to newer data against older values, we used coefficient α_t. It was found to minimize the two-hours-ahead forecasting error difference, in our case $\alpha_{t-4} = 0.4$, $\alpha_{t-3} = 0.6$, $\alpha_{t-2} = 0.8$, $\alpha_{t-1} = 1.0$. We did not re-adjust it for every day, just calculated it for the whole measurement period.

Fig. 8 shows the loads calculated two hours ahead by using (4), as well as the actual load and the forecast one day ahead. It is clear that (4) is reducing the difference between the day-ahead forecast and the actual load.

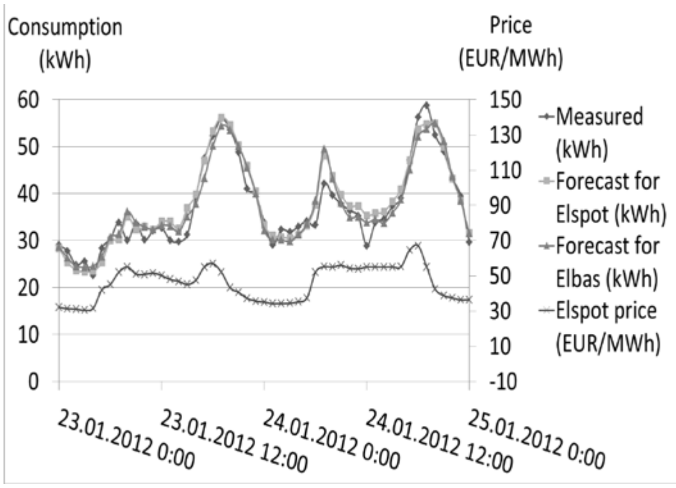

Fig. 8 Measured and forecasted consumption and Nord Pool prices during the period of January 23rd – 24th of 2012.

At the same time it should be noted that in certain situations, using (4) can cause a larger difference between the actual and the forecasted load. However, in general the formula reduces the error made by forecasting one day ahead.

Based on these results, we can summarize that in case of day-ahead forecasting, the use of the proposed forecasting method resulted in an average below error of -12.52% and in an average above error of +15.48% regarding the actual load.

The mean absolute percentage error (MAPE) is used for evaluating performance of the model. MAPE is calculated with the following formula [9], [10]:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{[l_e(t) - l(t)]\cdot 100}{l(t)}\right| \quad (5)$$

where $l(t)$ stands for actual load, $l_e(t)$ for mathematical load expectation, and N for population of the evaluation set.

When using (5) for forecasting two hours ahead, we got an average below error of -11.52% and an average above error of +9.97%. Meanwhile the MAPE for day-ahead forecasting was 14.17% and for two hours ahead 10.70%.

The Fig. 9 shows how volatile the MAPE actually is. Despite the relatively large MAPE of prediction, it is clear that the day-ahead forecasting coincides with the real load and the forecast made two hours ahead reduces the error made with day-ahead forecasting. The relatively large forecasting error is mainly caused by the very small number of surveyed consumers, since the stochastic variation in consumption of each consumer has a strong effect on the entire load curve of a set of consumers.

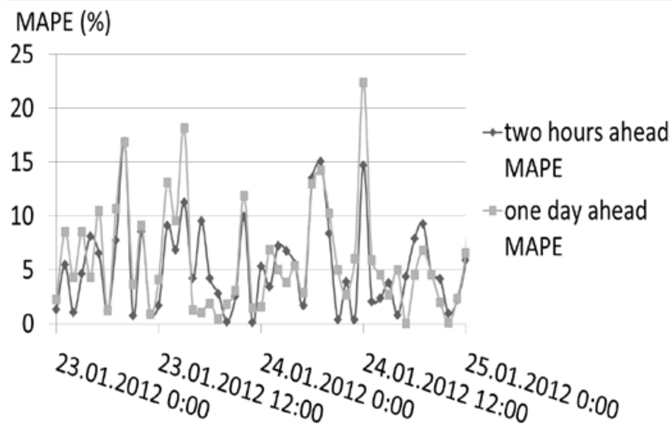

Fig. 9 MAPE for one-day-ahead forecast and two-hours-ahead forecast during the period of January 23rd – 24th of 2012.

V. Proposed Algorithm for Real-Time Pricing System

When considering the design of Nord Pool power exchange and the purpose of retail electricity sellers to sell electricity that is calculated on the same time interval and price as in power exchange, an appropriate model for forecasting one day ahead and an additional model for forecasting at least one hour ahead would be necessary. In this section we propose an algorithm that electricity sellers could use to offer consumers an electricity price on an hourly basis.

In case of a proposed real-time pricing system, the household's electricity price is calculated and sent to the consumer at the beginning of each time period. The interval may be 15 minutes, 1 hour or any of the currently suitable electricity market's trading periods. The consumer price changes in real time and lasts during the agreed interval. The price of the electricity would reflect on the network situation – the availability of wind power, the system load, generating capacity, temperature etc. Naturally, one important issue remains for end-users – the volatility of the electricity price. Most consumers are accustomed to fixed prices and know how to plan their costs. However, when electricity prices fluctuate within a large range per day, the planning will become much more complicated.

The differences between the load maximums and minimums are very big. In order to align and reduce the load curve and overall costs of the system, it would be necessary to move load from maximums to minimums. This would most likely be achieved through the price of electricity because the price will always remain the main interest of the consumer.

The development of the smart grids will mean a drastic change in power use and administration. Users will become active participants in energy management and will be able to control their consumption. On the other hand, utilities will be able to control demand peaks and manage the grid efficiently from generation to distribution [11].

A real-time pricing system would help consumers to plan their consumption in order to reduce their expenses on electric energy. The intelligent appliances and chargers can be controlled by the home controller in response to the distribution grid conditions and dynamic prices [12]. Concurrently, this would also help to smooth the load curve, meaning that a stronger demand response is accompanied. It is called the incentive-based demand response program if it is designed for the purpose of improving supply reliability and is called as the price-based demand response program for the purpose of preventing price spike [13].

Fig. 8 shows clearly that power exchange price is high exactly at the same time period when load is high and vice versa. Therefore when consumers would really sense the higher price during higher load periods they may move their consumption to lower load periods, which could lead to smoother load curve.

According to the current order in the Nord Pool energy market, the seller has to make the most accurate prognosis of consumption one day ahead and purchase the desired amount of electric power from the day-ahead market (Elspot). Then, during the day the sellers have to make the consumption prognosis 1 hour ahead and buy the necessary amount of electric power from intraday market (Elbas), if needed. This means that an hour before the delivery (real-time), the seller has to make the last transaction.

In Elspot, 12:00 central European time (CET) is the time of market closure for bids with the delivery for tomorrow. Simply put, the price is set where the curves for sell price and buy price intersect. The price is typically announced to the market between 12:30 and 12:45 CET with a 3-minute warning, after that the trades are settled. From 00:00 CET the next day, contracts are physically delivered hour by hour according to the contracts entered. Elbas is a continuous market and the trading takes place every day around the clock until one hour before delivery.

At the moment in Estonia, the balancing energy prices and amounts are calculated on the second business day by Elering. In addition, Elering provides the balancing service for balance responsible parties. Therefore the seller, who wants to offer consumers the tariff system, where the electricity price changes in real-time, will also need to predict balancing energy prices to calculate the price for the households. The prediction of balancing energy prices clearly bears a risk for the seller and is therefore included in seller's fee.

Thus, we propose that the energy price calculated by retailer would consist of three different components:

$$S_{E_{t+1}} = S_{t.elspot} + S_{t,elbas} + S_{Comission} \tag{6}$$

where $S_{t,elspot}$ stands for Elspot's electricity price, $S_{t,elbas}$ for Elbas' electricity price, $S_{comission}$ for seller's fee, which includes their expenses, profits and risks of balancing energy.

A seller for Elspot would prognose the consumption of consumers in their portfolio by using (3) and based on these predictions would make the needed transactions in Elspot. Thus, the price based on Elspot would be calculated by the formula:

$$S_{t,elspot} = f(l_{dem}; l_{\sup}) \tag{7}$$

where l_{dem} stands for power demand, l_{sup} for power supply.

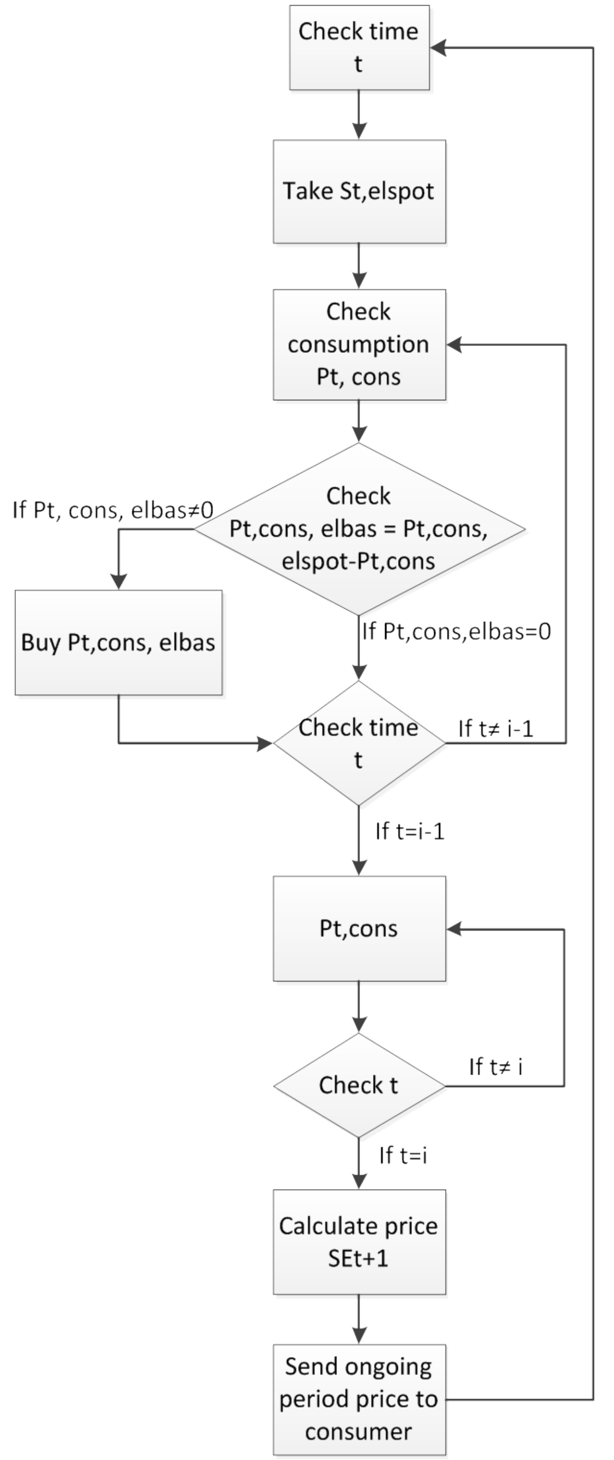

Fig. 10 proposed algorithm for calculating the electricity price and sending it to the customer.

In addition, a seller for Elbas would prognose the consumption of consumers in their portfolio by using (3) and based on these predictions would make the needed transactions in Elbas. Thus, the necessary amount required to be purchased from Elbas would be calculated by the formula:

$$L_{Elbas,t+2} = l_{Elbas}(t+2) - l_{Elspot,t+2} \quad (8)$$

where $L_{Elbas,t+2}$ stands for required power from Elbas, $l_{Elbas}(t+2)$ for predicted load for the next hour.

When $l_{Elbas}(t+2) = l_{Elspot,t+2}$, then the prognosis would stay the same as the predicted load for the next hour. Therefore, an additional transaction would not be necessary.

Electricity price calculation and notification of the customer would therefore take place in accordance with the algorithm shown in Fig. 10. The algorithm starts by checking the time, i.e checking the next trading period. On the previous day, the seller has carried out deals in Elspot market. So, the seller knows how much energy and at which price they have bought from Elspot for the next trading period. Then, the seller determines the current consumption and forecasts the consumption of consumers in their portfolio for the next trading period. If there is enough power, then time is checked and if needed, the seller can re-forecast and perform an additional control. If the power does not suffice, the seller will make an additional transaction in Elbas market, check the time again and if needed, the seller can re-forecast and perform an additional control. If t=i–1, then Elbas is closed for the next hour's trading period. The seller checks the consumption until t = i. If t=i, then the next trading period has started and the seller must notify consumers about the ongoing period`s electricity price. After the consumers have been notified, the seller can start calculating the price for the next period.

VI. CONCLUSION

In this article, we used regression analysis of time series to analyse a small group of consumers in order to create a model for forecasting load one day ahead and two hours ahead. Usually, the research has been carried out based on the whole system or on a part of the system. The current study, however, was carried out with the help of remotely readable meters and analysed individual consumption of eleven private houses and one apartment building with 60 apartments in a village in Estonia during 2012.

Our work shows that in Estonia, the load of home users and the outside temperature have a strong correlation. Surely, there are a lot of other factors that affect consumption of consumers like for example wind, daylight etc. However, since the effects of these factors on load are even more difficult to assess, temperature dependence was chosen to be the basis of this research.

Based on this study, we can conclude that in case of two-hours-ahead forecasting, the use of regression analysis of time series model resulted in a lower average below error and average above error regarding the actual load than when forecasting one day ahead. MAPE for two hours ahead forecasting was also lower compared to forecasting one day ahead. Regardless of the fact that a very small number of customers were analysed and their effects on load curves were quite significant, we are very pleased with the results. We believe that with a greater number of consumers, the resulting prediction error of the proposed method will probably be significantly reduced.

In regards of forecasting accuracy, the results of this work cannot be compared with results of studies where models and forecasting are based on whole power system load or on a large part of the power system load. Forecasting based on the entire power system load, which has a large number of different stochastic changes in the load, implies that the system load is not strongly affected by individual consumer load changes.

The electricity price at the power exchange is volatile and it is impossible to forecast next year`s electricity price, since it depends on many different factors. It is clear that intraday exchange market price fluctuates and during some time periods the prices may be cheaper than current open market fixed or power exchange average price tariffs and on other periods they could again be more expensive [14]. This means that the real-time tariff system gives customers the opportunity to manage their consumption in order to keep their electricity costs as low as possible.

Currently, the price packages offered to consumers do not reflect on actual electricity production costs. However, it is important to offer price packages which take the network situation into account and move consumption away from peak load and fulfil minimum load. Therefore, to achieve a better demand response it is important to offer either more daily rate price packages or a real-time pricing package. The algorithm proposed in this work could be used to offer consumers real-time price packages, without the need for any changes in power exchange rules.

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