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ELECTRICAL ENGINEERING, MINING ENGINEERING D66

Real-Time Electricity Tariff System for Retail Market

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Declaration:

Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for any academic degree.

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TANEL KIVIPÕLD

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LIST OF ORIGINAL PUBLICATIONS

The present doctoral thesis is based on the following publications, which are referred to in the text using Roman numbers I-VI:

- [I] **Kivipõld, T.**, Valtin, J. Replacement of the Regulated Price of Oil Shale-Based Electricity With Open-Market Price and Real-Time Tariff System Opportunities. *Oil Shale*, Vol. 30, No. S2, 2013, Estonia, pp. 195-210.
- [II] **Kivipõld, T.** Overview of Intraday Variable Tariff System. 13th International Symposium "Topical problems in the field of electrical and power engineering", Doctoral School of Energy and Geotechnology II: in memoriam of professor Juhan Laugis. Pärnu, Estonia, January 14-19, 2013, pp. 236-237
- [III] **Kivipõld, T.**, Valtin, J. Regression Analysis of Time Series for Forecasting the Electricity Consumption of Small Consumers in Case of an Hourly Pricing System. In: *Advances in Automatic Control, Modeling & Simulation: Proceedings of the 15th International Conference on Automatic Control, Modeling & Simulation (ACMOS '13)*. Brasov, Romania, June 1-3, 2013, pp. 127-132.
- [IV] **Kivipõld, T.**, Niitsoo, J. Overview of information and communication issues for smart grid solutions. 10th International Symposium "Topical Problems in the Field of Electrical and Power Engineering", Doctoral School of Energy and Geotechnology II, Pärnu, Estonia, January 10-15, 2011, pp. 108-112.
- [V] **Kivipõld, T.**, Valtin, J. 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. *International Journal of Energy and Environment*, Issue 5, Vol. 7, 2013, pp. 221-228.
- [VI] Vaimann, T., Niitsoo, J., **Kivipõld, T.**, Lehtla, T. (2012). Power Quality Issues in Dispersed Generation and Smart Grids. *Electronics and Electrical Engineering*, Vol. 18, No. 8, 2012, pp. 23 - 26.

In the Appendix B, copies of publications I-VI are included.

Author's own contribution

The contribution by the author to the papers included in the thesis was as follows:

- [I] Tanel Kivipõld wrote the paper and was the main author. He was responsible for the literature overview, data collection, calculations and analyses.
- [II] Tanel Kivipõld wrote the paper and was the main author. He was responsible for the literature overview, data collection, calculations and analyses. He made the presentation of the paper at the 13th International

Symposium "Topical Problems in the Field of Electrical and Power Engineering" in Pärnu, Estonia in 2013.

- [III] Tanel Kivipõld wrote the paper and was the main author. He was responsible for the literature overview, data collection, calculations and analyses. He made the presentation of the paper at the 15th International Conference on Automatic Control, Modeling & Simulation in Brasov, Romania in 2013.
- [IV] Tanel Kivipõld wrote the paper and is the corresponding author. He was responsible for the literature overview, data collection, calculations and analyses. He made the presentation of the paper at the 10th International Symposium "Topical Problems in the Field of Electrical and Power Engineering" in Pärnu, Estonia in 2011.
- [V] Tanel Kivipõld wrote the paper and was the main author. He was responsible for the literature overview, data collection, calculations and analyses.
- [VI] Tanel Kivipõld wrote the paper and is the corresponding author. He was responsible for the literature overview, data collection and analyses.

INTRODUCTION

In most countries, the generation, transmission, distribution and sale of electricity have been a monopoly for a long time. Until quite recently, electricity transmission and distribution have been a natural monopoly and there has been no economical reason to create a market or boost competition between different grid operators. But over the few past decades, electricity generation and selling have gone through significant changes and today there are functioning power exchanges and open retail markets throughout the world. The European Union directive 2003/54/EU [1] requires that every European Union Member State should have an open electricity market.

In 2013, Estonian electricity market opened fully and it opened up possibilities for an open retail market as well. Today, participants in the Nord Pool Spot include Estonia, Latvia, Lithuania, Finland, Sweden, Denmark and Norway. In the Nord Pool Spot exchange, every trader can offer the electricity he produces.

In the competition-governed market economy conditions, the increase of electricity prices is expected to decelerate. The price is formed on competitive terms and depends on the cost of production. In Estonia, a functioning retail market is still under completion. For example, in 2013 the state-owned Eesti Energia AS held 71.9% of the balanced electricity portfolio, and in January 2014, its share was 60.0% [2]. So, the size of Eesti Energia's portfolio is decreasing and that of various retailers is increasing as seen in Table 1, Appendix A. Therefore, one can note that competition in the retail electricity market is gradually growing.

In Europe, the transition to an open electricity market began in 1990. Similar patterns in the market have been encountered with and similar concerns endured by early openers, as well as by those that have opened in recent years. In most cases, the electricity price has increased and problems with implementing competition have occurred. The consumers are often not sufficiently informed and, as a consequence, they do not actively participate in the retail market, i.e. they are not choosing between different retailers. As a result of liberalization in the open market, retail electricity prices not always fall in nominal terms. In some countries, regulated prices were inefficiently low, discouraging investment and encouraging wasteful consumption. In these cases, liberalization led to higher prices and better incentives [3].

In theory, an open market enables consumers to choose from different retailers. In the open market, price formulation rules are changed. In case of power exchange, the principle is that the better the availability of generation the lower the price. In case of a closed electricity market, all the consumers buy electricity with a fixed tariff, while the electricity price is submitted by the producer to the relevant government agency for approval that eventually approves it (in Estonia the Estonian Competition Authority). In case of power exchange, the price is changing every hour and in theory, the consumers are can affect the price.

In an open market situation, the price of electricity depends on many factors. Unlike ordinary products available on store counters, electricity is a unique product, which is characterized by the following:

- Electricity is produced and consumed synchronously at the same time and rate and proportionally, continuously and uninterruptedly all the time.
- It is not possible to store electricity in large quantities in an economically feasible way.
- Power consumption depends on the time it takes place (day/night, weekend, season, year) and is characterized by the respective consumption patterns.
- Electricity cannot be traced, i.e. one cannot determine the station where the electricity consumed was produced.
- There is always the possibility of large-scale power system failure the power system management needs to take into consideration.

The main factors affecting the price of electricity in the open electricity market and power exchange are the adequate capacity available and electrical connections, both domestic and with neighbouring areas, to ensure the movement of electricity. In Nordic countries, for example, hydropower's availability has a significant impact on Nord Pool Spot prices.

Despite the liberalization of electricity market, there are no new tariff systems for consumers and all the existing tariff systems or price packages are based on the tariff systems used earlier. Since the latter systems do not take into account costs of electricity production at the moment of consumption, it is necessary to create a tariff system which considers such costs. In short, prices should reflect the short-run marginal cost of production [4, 5]. In other words, buyers' electricity costs should not exceed the production and delivery costs of electricity [6]. The term "real-time tariff system" has not been properly defined. To avoid misinterpretation, this has to be done well. In addition, it needs to be determined how and how often the price should change.

The purpose of the thesis

The main purpose of this thesis is to propose an algorithm for real-time tariff system, to find out possibilities of forecasting electricity consumption by using historical measurement data as input and to evaluate the potential of real-time pricing (RTP) for smoothing the load curve. The thesis gives a description of RTP and offers a solution to implement it.

The more specific goals of the applicant's doctoral studies were:

- to propose the definition of RTP;
- to develop an algorithm for RTP system for retail market;
- to propose a method for retailers for forecasting household electricity consumption (by retailers siin on veidi eksitav, kui siis for, aga võib ka ettepoole viia.) and to analyze its possibilities;
- to analyze the potential of RTP for smoothing the load curve;
- to analyze the economic feasibility of the RTP system for households.

This doctoral thesis is based on six published papers written by the author of the thesis. The respective researches were carried out among Estonian consumers during the years 2009–2014.

Outline of the thesis

The current thesis includes a summary chapter and six appended published papers. In the Summary chapter, the related author's publications, methods and results are described. The thesis includes additional analyses, which have not been previously published.

In Chapter 1 *Material and Methods*, the background information, calculation methods and description of load-weather dependence are given. RTP is compared to conventional tariff systems, and its advantages and disadvantages are shortly described. Price-managed electricity consumption is described. An overview of the methods for forecasting electricity consumption is given. An overview of the modeling software used is presented.

In Chapter 2 *Results*, the outcomes of the current work are presented. The definition of RTP system is formulated. The description of the algorithm proposed for RTP according to current power exchange rules is given. The method (regression analysis of time series method) for forecasting load is presented. The electricity consumption data gathered in Estonia as well as load-weather dependence are analyzed. The method proposed for correcting the regression analysis of time series method is described. The results obtained using the regression analysis of time series method for load forecasting and the respective correction method are presented. Estimation of the influence of RTP on smoothing the Estonian load curve is performed.

In Chapter 3 *Discussion*, issues arisen during the study are analyzed and the critical assessment of the results is made. Data used for the analysis originated from the database of Statistics Estonia, as well as from papers published in scientific journals, other pertinent research works, legal acts of Estonia, and doctoral theses.

The study was carried out performing calculations in Excel and using the modeling software to verify the results obtained and to evaluate the accuracy of the forecasting models used.

Metering systems and necessary communication solutions, related financial aspects included, are not considered in the thesis. This is because according to the Estonian Grid Code, new metering systems should be installed by the distribution network operator (DNO) only by 2017 [7] and the respective issues on the State level have not been decided yet. According to the Electricity Market Act, the remote read meter is a measuring device that stores information on consumed electricity for trading periods, and enables readings to be automatically forwarded [8].

Contribution of the thesis

This thesis includes theoretical approaches, and methodological as well as practical recommendations for the further development of RTP systems. The

originality of the thesis consists in theoretical and practical results. The majority of studies carried out before have been based on theoretical knowledge and assumptions or on using system load or part of system load information as study input [9–12]. In the present work, actual consumption data were used as input to carry out necessary analyses.

Theoretical originality includes methodological recommendations for developing an algorithm for RTP. The results obtained expand the existing knowledge about the definition of RTP and estimation of its positive effects. Theoretical methodology includes an approach proposed for forecasting household electricity consumption, using the real-time algorithm developed.

Practical originality of the thesis includes results obtained employing the proposed approach for forecasting household consumption by using actual weather and household consumption data. The results of the thesis can be used by retailers to develop new forecasting methods to offer real-time price packages, employing the proposed algorithm.

The current relevance of the thesis is related to the recently liberalized retail market in Estonia, as well as new metering systems being installed and possible smart grids to be developed. The proposed algorithm and development of forecasting models could help solve the problem of how to offer consumers real-time price packages. The results will be useful for retailers and the researchers concerned. Currently, uncertainty in the economy and rising energy costs are requiring new approaches to offer consumers the flexibility and opportunities to control their costs.

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Finding time for performing the research and writing papers and this thesis has been a great challenge besides work and family. I would like to thank Piia, my parents, brother and sister for support and understanding during all this time.

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1. MATERIAL AND METHODS

1.1. Overview of Estonian electricity market and different tariff systems

In papers [I] and [II], the different tariff systems used earlier and available currently in Estonia, as well as various conditions applicable in Estonian closed and open electricity markets, including power market (Nord Pool Spot) pricing rules, are analyzed.

Wholesale and retail electricity markets have been free for some time already and function without problems. Since April 1, 2010, an open consumer has had the right and obligation to choose an electricity seller from among other retailers. Back then, an open consumer was a consumer that used at least 2 GWh of electricity a year at consumption sites through one or more connection points. Until 2013, open consumers accounted for about 30% of Estonia's electricity consumption. From January 1, 2013, all consumers are open and purchase electricity at the liberalized electricity market [I].

In Estonia, oil shale-based electricity still constitutes a major part of the total electricity produced (Figure 11, Appendix A) and consumed. Therefore it can be stated that the rate of electricity largely depends on oil shale-based electricity generation. However, the use of oil shale for power generation is gradually decreasing. In 2010, the oil shale percentage in electricity production was 92%, in 2011 it was 85% and in 2012, 81% [13]. One reason for the decrease is definitely the increasing use of renewable energy sources. However, oil shale-based electricity is still competitive in the open electricity market. Since 2010 its export to Latvia has increased from 1555 GWh to 2500 GWh, and to Lithuania, from 1140 GWh to 2022 GWh until 2012. The export to Finland has decreased from 1659 GWh to 428 GWh but this drop is due to Finland's lower electricity price compared to Estonia's.

In the open electricity market, the price of electricity is no longer controlled by the State. Instead, it is formed on the market and power exchange. Unfortunately, the opening of the market was also accompanied by the increase of electricity price since for the home user the regulated market price was lower than the current power exchange price. In 2012, the Estonian Competition Authority set the average sales price limit of the electricity produced by Narva Power Plants to 29.4 EUR/MWh [14]. There were 36 power companies in the closed electricity market in Estonia and the average approved price of electricity was 32.9 EUR/MWh [14]. However, in 2012 and 2013, the average price of electricity in the Elspot Estonian region was 39.2 EUR/MWh and 43.14 EUR/MWh, respectively, i.e. on average over 25% higher than the Estonian Competition Authority approved average price. At the same time the average system price on the Nord Pool Spot was 31.2 EUR/MWh in 2012 and 38.10 EUR/MWh in 2013. In Finland area, the respective prices were 36.64 EUR/MWh and 41.16 EUR/MWh.

Since in the retail market the sellers are competing with each other, the price for households is determined on competitive terms. Today there are 12

electricity sellers in Estonia. Although in the open market households may choose between electricity packages offered by many retailers, it is unfortunate that they have to choose only between different fixed electricity price packages whose prices change monthly or even more seldom.

Conventional price packages currently offered to retail consumers do not mirror actual costs of electricity production. Retailers offer price packages which involve generally only two rates – daily and nightly. In [15] it was found that time of use (TOU) rates capture only 20% of the efficiencies of RTP. Regarding the development of future smart grid and increasing distributed generation (including biomass, wind and solar energy use), it would be rational that the users plan consumption and pay according to the actual costs of electricity production.

The open power market introduced two additional price packages that are based on conventional price packages. Retailers offer consumers an electricity price that depends on one of the following:

- average power exchange price for the previous day, week or month, which may include daily and nightly tariffs and the electricity price applies to the period used in calculations;
- combined price in case of which 50% of the electricity consumed in the billing period (month) is priced with a fixed price and the other 50% is priced with an average power exchange price in the previous billing period.

Naturally, there is a need for new metering systems, which are able to fix the amount of electricity consumed during the respective interval. In [II] it is stated that by the end of 2017, installation of remote read metering devices will be finished, which should give a green light to many innovative possibilities, e.g. electricity consumed can be measured within a desired interval or consumers can be switched on or off the system. Hence, soon DNO should be prepared for taking electricity meter readings during the required interval. Additionally, it will be necessary to establish rules and work out information systems, which could provide consumers with RTP.

RTP has several advantages over conventional price packages. In [II] it was pointed out that RTP will possibly help achieve the following goals:

- reduction of consumer electricity costs by managing electricity consumption and moving load to off-peak price periods;
- motivation of consumers to manage consumption by a more volatile price;
- increase of consumer electricity usage efficiency by managing electricity consumption and introducing the latest technologies to the household;
- increase of consumer demand response (DR) according to changes in the electricity price;
- approximation of load curve by moving load to off-peak price periods;
- limitation of peak load and smaller load minimum by moving load to off-peak price periods;

- reduction of balancing electricity storage costs by moving load to off-peak price periods;
- increase of wind and solar power integration by consuming more electricity at the time of availability of wind and solar power.

In implementing the RTP system one may encounter various difficulties. Paper [IV] gives an overview of problems accompanying the growth of the information amount to be communicated. In addition to recording and forwarding load and pricing information, new metering systems can also forward information about power quality, automatic fault identification, etc. In [VI], an overview of power quality issues in case of distributed generation is presented. On the other hand, there are benefits regarding the additional information gathered, such as a better overview of energy consumption efficiency, monitoring of electricity consumption and related costs, finding electricity wasting devices and controlling building's electricity consumption.

Traditionally, information moves from the metering system to the network operator. But new metering systems will allow sending information also to consumers. Therefore, the new metering systems with data movement in both directions likely require rebuilding of the existing grid communication systems [16]. Bottlenecks, however, will be metering and communication systems, which are still being developed and constructed and might not meet the needs of the real-time tariff system once it is available. One solution would be using power line communication (PLC) [17] which enables data to be forwarded through electrical cables. The biggest DNO in Estonia, Elektrilevi, is planning to use mostly the PLC technology and, to a lesser extent, meters which use mobile communication channels [18]. DNOs have to continuously deal with the problem and should also be prepared for future developments in order to avoid a situation where, for example, the devices installed allow no functioning of the new tariff system. An overview of different communication systems used in an electrical grid can be found in [19] and [IV].

In addition to different communication systems, it is essential to pay attention to security. A comprehensive overview of distribution grid security issues is provided in [20–23]. Communication systems have become vulnerable to cyber-attacks, and thereby the households' privacy is violated. In addition to recording and forwarding private information and consumption data, some of the remotely accessed meters are also able to turn off the power. Furthermore, the critical infrastructure system could also be jeopardized. Therefore, it is essential to identify potential risks in order to work out necessary security measures.

1.1.1. Real-time and conventional tariff systems

Consumers are accustomed to conventional tariff systems because these are easy to manage and comfortable to use. The fixed tariff offered to consumers by retailer for an agreed period is based on the following:

- average power exchange price in the previous month;
- retailer's prognosis of the average price for the upcoming period.

On the power exchange, the price is volatile and depends on various factors, such as power demand, transmission capacity, weather conditions, fuel prices, etc. In different geographical regions different factors influence the price on the power exchange.

Power price volatility or spikes cannot be avoided even in perfect markets. It is important to understand, from historical data, the formation of competitive electricity prices in different power markets. For example, price volatility in the electricity market varies hourly, daily, weekly, and seasonally. Most factors contributing to uncertainty are reflections of the regular fluctuation of power loads. The periodic fluctuation could be considered as the deterministic component of electricity prices. Furthermore, electricity prices have a number of instant price spikes with a long-term mean reverting trend, which is the random component and results from the physical characteristics of the power system, such as unusual demand, unexpected generator outages and transmission constraints. Factors affecting the fluctuation of random price result from not only load conditions, but also supply conditions [6].

In [24] it is stated that compared to fixed rates, RTP shifts price risk from the utility to the customer. With such a change one has to ask if there is an optimal time of advance notice of prices, whose fixing is necessary to avoid situations where customer would pay for electricity consumed during an hour when prices hit an extreme spike. The description of such situations can be found in [25].

Thus, for the customer the main difference between RTP and conventional tariff system is in price volatility which he has to get used to and learn to take advantage of. Analysis made in [1] showed that depending on consumer load curve, RTP could help save costs and that even without planning consumption. In addition, in Chapter 2.2 the dependence of fixed price and RTP on different consumer load curves is analyzed.

1.1.2. Managing electricity consumption by price

The objective of demand response (DR) is to make users react to changes in electricity system conditions. Usually, the purpose is to limit electricity consumption during certain periods, e.g. periods of transmission system limits or insufficient generation capacity availability.

DR can be classified as [26]:

- Incentive based programs (IBP)
 - Classical
 - Direct control
 - Interruptible/curtailable programs
 - Market based
 - Demand bidding
 - Emergency demand response
 - Capacity market
 - Ancillary services market
- Price based programs
 - Time of use

- Critical peak pricing
- Real-time pricing
- Extreme day critical peak pricing
- Extreme day pricing

In the past, DR was accomplished by either direct load control (feeder switching, by dispatch instruction) or frequency actuated relays. The end users, in most cases, are not compensated for disruptions, which are generally caused by connection failures. Deregulation and restructuring of markets has witnessed a change to a more market based approach to DR that has increasingly focused on incentive and price based DR [27]. TOU power price is widely applied in many countries and is considered as one of important approaches of demand side management [28].

In [VI], the potential spreading of dispersed generation in the future and probable accompanying power quality issues are described and analyzed. Due to the increasing spread of distributed generation, power quality issues will emerge. On the other hand, different fuels will be used to produce electricity and the price of electricity will vary even more on the power market. Paper [VI] suggests that the potential of distributed generation relies mainly on using non-fossil and renewable fuels, such as wind, litter oddments, wood, hydropower, etc. The availability of renewable energy, such as wind and hydropower, is inconsistent and unpredictable, which means that the electricity price on the power market will also be more fluctuating. But RTP will enable consumers to manage consumption by shifting it to a lower price period.

One of the goals RTP should help achieve is increasing DR since the fixed rate tariff system does not motivate consumers enough to plan consumption. This means that for the consumer, there is no difference between consuming electricity during the high price (peak load) or low price (minimum load) period on the power exchange. Thus, it can be said that the tariffs currently offered are not attractive enough to control consumption. Therefore, it is important to offer price packages which would take into account the system situation and make consumers shift consumption away from peak load. Due to the potential economic benefits the real-time electricity price could bring to the demand side, consumers would optimally adjust the electricity consumption of residential appliances by participating in the real-time price based DR program [29]. In conclusion, to achieve a better DR it is important to offer more daily rate price packages or a RTP package. Of course, the effect will also depend on the consumer's price sensitivity and on whether the consumer has the possibility to shift consumption to a lower price period.

The real-time tariff system clearly increases the consumer DR. Therefore, the real-time price smoothes the peak power demand and fills the low point of power demand. This peak clipping could reduce the investment in power system equipment and both peak clipping and low-point filling effect may improve load rate [30]. Furthermore, there are studies like [29] which have concluded that real-time DR can contribute to achieving lower electricity bill cost compared to fixed rate electricity price. In addition, some studies [31, 32] have assessed the

possible effect of DR on load forecasting accuracy. And finally, it can be concluded that a smoother load curve means smaller overall costs of electricity production and that grid operators can optimize the network capacity.

1.2. Methods for forecasting electricity consumption

In case of RTP retailers have to forecast electricity consumption for an upcoming period. Forecasting of electricity consumption is difficult since there are numerous factors that affect consumption and it is largely random in addition. Moreover, different consumers have different consumption habits.

In constructing models for forecasting load it is necessary to take the following load changes into account [33]:

- regular changes, like day-night, weekly and yearly fluctuations, trend and nature of the load on national holidays;
- temperature dependence, including temperature dependence inertia, nonlinearities and time variations, especially in case of electrical heating;
- dependence on operating values, which is expressed as load voltage and frequency sensitivity;
- randomness, which means random load changes that can not be forecasted;
- manoeuvrability, which means basically transmission grid node load changes that are caused by switching in distribution grid.

Random load changes are particularly noticeable in loads of small distribution grids. In case of random changes the relationship of the square deviation of small distribution grids loads towards mathematical load expectations is quite high. In case of small loads, hard slopes can be present that are not compatible with the normal distribution.

Load can be treated as a certain object, which can be characterized by general data, load data and a mathematical model of load. General data consists of the name of the load, connection point, marginal power, the type of the load, electricity consumers composition, etc. Load data describes all kinds of quantitative information about the load. Quantitative information includes, in particular, active and reactive power and current as well as bus voltage, outdoor temperature, and other values, which are used for load treatment. Load data may be both regular (time series), and nonregular, single data (e.g., yearly energy, minimum and maximum values, etc.). Load is often considered in a narrower sense than power or current [34].

Until recently, forecasting consumption was necessary for utility companies and network and system operators for constructing and maintaining the grid. However, in a liberalized electricity market, there are electricity sellers competing on the retail market. Thus, buying electricity from the power exchange and reselling it to consumers requires good forecasting models for electricity demand. Since retailers have a good overview of their consumers' habits, forecasting should be easier and more accurate [V]. The accuracy of

forecasting will improve even more with new metering systems, which allow recording electricity consumption in a desired time interval.

In [V] and [35], different forecasting methods that are based on regression analysis, time series, neural networks, Box-Jenkins models, expert system approaches and artificial neural networks (ANN) are described. The most commonly used forecasting techniques are neural network algorithms, time series approaches, regression techniques and expert system approaches [36]. A method is chosen primarily on the basis of the character and volume of source data, and expected results (time and accuracy of forecasting, etc.). The time series and regression techniques are the two major classes of conventional statistical algorithms, and have been successfully applied 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 ANN over expert systems is its nondependency from an expert. Furthermore, ANN performs nonlinear regression among load and weather patterns and can be used to model the time series method or as a combination of both [37]. During each forecast ANN models learn and generalize and abstract information from data. ANNs are strengthening or weakening interconnected weights during the forecasting that connect processing inputs of the model

If weather conditions are taken into account in forecasting the load, then the load is given in the following form [37]:

$$l(t) = l_{ir.}(t) + l_{w. ind}(t) + l_{w. dep.}(t) + l_{noise}(t), \quad (1)$$

where $l_{ir.}(t)$ – irregular load changes in the future,
 $l_{w. ind.}(t)$ – weather-independent component,
 $l_{w. dep.}(t)$ – weather-dependent component,
 $l_{noise}(t)$ – noise residual or stochastic component.

Difficulty in forecasting load arises due to its nonlinear and irregular variation [38] the predicting of which is complicated, if not impossible. In [39] it is concluded that the temperature dependency model can be used for calculating temperature influence in the load analysis and short-term forecast processes, when the actual or meteorologically forecasted values of temperature are known.

1.3. Data measured in Estonia and load-weather dependence

The current research is based on measurements taken in Loo village near Tallinn during January 1–December 31, 2012. Altogether, the individual consumption of eleven private houses and one apartment building with 65 apartments was measured. Measurements were taken every hour, using remotely accessed single-phase electricity meters P515.23D – 1E1 ALNI. This particular apartment building was a stone house with central heating; the

apartments had a furnace or a fireplace and an oven. The main fuse of one apartment was 25 A.

The aim was to create consumer load curves and analyze their behavior. It was observed that the consumption started to rise on workdays at 1 p.m. and achieved maximum by 3 p.m. Starting from 7 p.m. the consumption decreased until 9 p.m. On weekends, the consumption began to rise at 7 a.m., increasing till 9 a.m. and started to fall at 6 p.m., decreasing until 7 p.m. [I]. As shown in Figure 1, the load curve for the monitored consumers and Estonian load curve are quite similar, and the consumption peaks are in the higher price rate periods of the market. The monitored consumption peaks occur with small delays compared to system peaks.

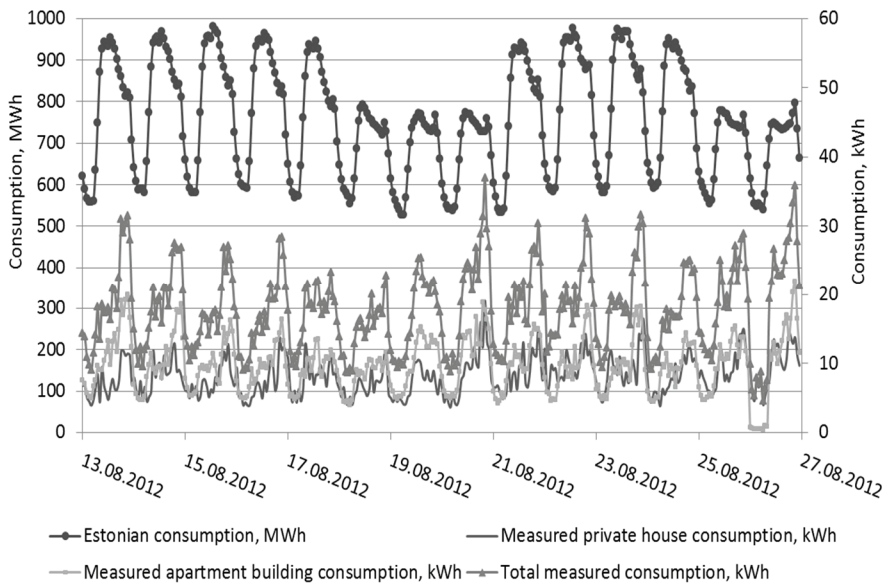


Fig. 1. Estonian whole power system load and measurements carried out in Loo village during the period August 13–27, 2012.

In this thesis, the dependence of load on temperature is analyzed. For this, meteorological data from the Estonian Meteorological and Hydrological Institute’s meteorological station in Harku were obtained. In [III] and [V], load-temperature dependence was preliminarily assessed. To find out whether load really depends on temperature, the corresponding correlation was found. The aim was to use these dependents as inputs for load forecasting. This is discussed in Chapter 2.3 of the thesis.

The whole measurement period was one year, i.e. 8784 hours. After sorting out various erroneous measurements, 6497 hours of data, i.e. 74%, could be subjected to further processing. Most of the erroneous measurements were caused by failures of remotely accessed single-phase electricity meters, because occasional disturbances occurring in the building’s electrical installation distorted the information sent through power cables. Usually, some readings of individual meters were missing. However, all of the hourly data containing any

missing information were excluded. Some of the measurements were eliminated because of the missing outside temperature data.

1.4. Use of Statistical Package for Social Sciences for forecasting electricity consumption

In this doctoral thesis, Statistical Package for Social Sciences (SPSS) software was used, in addition to Excel, to model the dependence of apartment building and household consumption on outside temperature. SPSS was mainly used to test the equations created in Excel and to evaluate the accuracy of models.

SPSS is a software package used for statistical analysis. It is a forecasting and modeling program that enables analysts to predict trends and develop forecasts. SPSS helps create sophisticated forecasts that take into account different variables, such as weather conditions, time of day, year, etc. Experienced forecasters can use SPSS to validate the models they use. In addition to statistical analysis, data management (case selection, file reshaping, creating derived data) and data documentation are features of the base software. SPSS provides operating model analysis accuracy reports. Statistics included in the base software are:

- descriptive statistics: descriptives, frequencies, cross tabulation, explore, descriptive ratio statistics;
- bivariate statistics: means, t-test, analysis of variance (ANOVA), correlation (bivariate, partial, distances), nonparametric tests;
- prediction of numerical outcomes: linear regression;
- prediction of identifying groups: factor analysis, cluster analysis (two-step, k-means, hierarchical), discriminant.

2. RESULTS

2.1. Definition of real-time tariff system

One of the purposes of the thesis was to define RTP. The term “real-time pricing” is not new and has been in use for decades. However, in this work it is defined according to the proposed algorithm. Electricity tariffs were originally intended for the taxation of the electricity consumed. In a closed electricity market where the producer’s price for electricity is approved by the regulator, it is perhaps not so important that at every moment of time the electricity price correspond to the generation expenditure. Of course, in a closed market situation the variable tariff system would increase DR. In Estonia, the liberalized electricity market and power exchange, on the other hand, have expanded the circle of producers who are using different fuels for electricity production (Figure 11, Appendix A) and therefore their production costs are different. This means that the electricity generation costs vary intraday according to demand, which is a decisive factor in picking out producers that generate electricity for the power market (Nord Pool Spot). In [I] it was pointed out that in 2010, 92.3% of the electricity in Estonia was produced from oil shale. By the end of 2013, in the Estonian electricity system 274 MW of wind farms had been installed.

The term “real-time tariff system” may be somewhat confusing. One cannot at any moment of time calculate current electricity production costs. However, in the power exchange it is possible to calculate the regional electricity price for the next time interval. Therefore, it can be said that "RTP" means retailer charges for delivered electricity that vary hour by hour and are determined on the basis of power exchange prices, using an approved algorithm.

The real-time tariff system is reflecting the cost of electricity production for every consumer for an agreed time interval, to which network and other charges are added.

The description of the RTP algorithm proposed for Estonia is given in [I] and discussed in Chapter 2.2 of the current thesis.

2.2. Algorithm developed for real-time pricing

In this section, an overview of the elaboration of an algorithm for RTP is given. The main objective of developing the algorithm was to minimize household electricity costs, to take into account power exchange rules and to induce stronger competition between retailers. For this, market and power exchange rules were also analyzed. The proposed algorithm will not require extensive changes in the rules of retail market or power exchange.

According to the current rules of the power market (Nord Pool Spot) the retailer has to make the most accurate prognosis of consumption one-day-ahead and purchase the desired amount of electricity from the day-ahead market, Elspot. Then, during the day the retailer can make the consumption prognosis one hour ahead and buy the necessary amount of electricity from Elbas, if needed. Elbas is a continuous market and the trading takes place every day

around the clock until one hour before delivery [40]. This means that one hour prior to the delivery (real-time), the retailer has to make the last transaction.

Presently in Estonia, balancing electricity prices and amounts are calculated on the second business day by TSO. TSO provides transmission services to producers, DNOs and corporate consumers in Estonia. For example, there is a balancing market in Finland, and the prices of the balancing power are publicized primarily on Nord Pool Spot's website no later than two hours after the hour in question [41]. In addition, TSO provides the balancing service to balance responsible parties. Therefore, the seller wanting to offer consumers a tariff system whose electricity price changes in real time, will need to take into account balancing electricity prices to calculate the price for households. The prediction of balancing electricity prices clearly bears a risk for the seller and is therefore included in the seller's fee.

The proposed RTP system is a system which calculates household electricity price and sends the respective information to the consumer at the beginning of each time period. The interval is one hour as is the trading period on the power market, i.e. the consumer price changes every hour. Therefore, the price of electricity would reflect the network situation availability of wind power, system load, generating capacity, temperature, etc. In addition, there are power exchanges where the trading period is shorter, e.g. New Zealand's electricity market (NZEM), Australian electricity market and APX Power UK Spot have a trading period of 30 minutes [42–44].

In the current thesis, the renewed algorithm is presented. In Figure 2, the proposed algorithm and retailer's steps in one day when providing RTP to consumers are visualized. The first version of equations and the algorithm for price formation are presented in [I]. If the trading period is one hour, then according to the proposed algorithm, one day needs 24 models. If the trading period is shorter than one hour, it would need even more models. Shorter trading periods can help achieve higher load forecasting accuracy. In [45] it is concluded that using a 15-minute interval for gathering consumption data clearly provides higher forecasting accuracy than using a one-hour interval.

The algorithm starts with forecasting load for the next 24 hours. Then, the retailers carry out transactions in the day-ahead market (Elspot). Then, the seller determines the actual load information two hours before the ongoing price period. Having the information on the difference between actual load and previous forecast, the retailer can correct the forecast for the ongoing price period, using the proposed correction method described in section 2.3.3. Afterwards, the seller examines whether the power purchased from the day-ahead market is sufficient, using the following equation:

$$\Delta l(t) = l_{24h}(t, d) - l_{2h}(t), \quad (2)$$

where $\Delta l(t)$ – difference between one-day-ahead forecast and the two-hours-ahead correction of forecast;

$l_{24h}(t, d)$ – hourly consumption, depending on the time of day and the weekday, kWh;

$l_{2h}(t)$ – two-hours-ahead correction of the one-day-ahead forecast, kWh;
 t – ongoing price period.

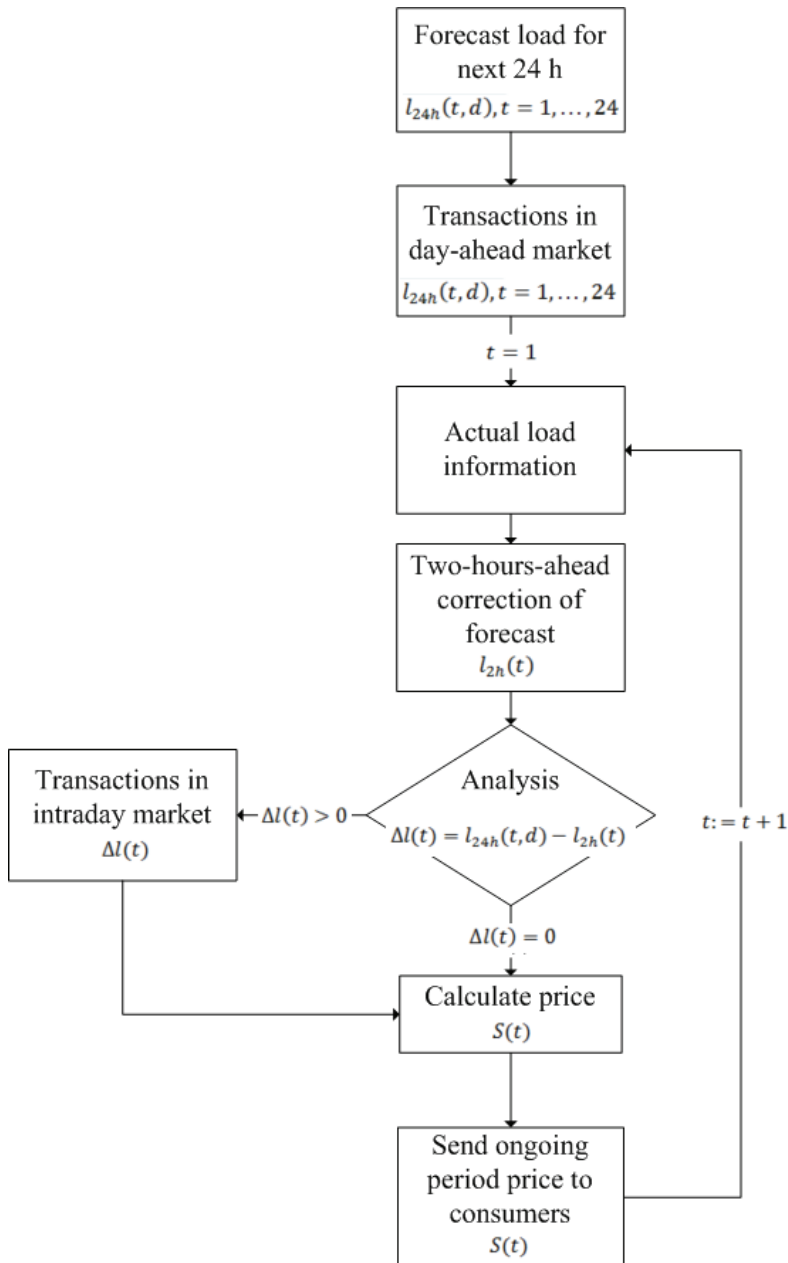


Fig. 2. Proposed principal one-day-ahead forecast algorithm for RTP.

If enough power was purchased, i.e. the condition $\Delta l(t) = 0$ is satisfied, then it is possible to calculate the price for the ongoing time period. If there is a difference between one-day-ahead forecast and two-hours-ahead correction of

the forecast, i.e. $\Delta l(t) > 0$, then the seller will make an additional transaction in the Elbas market and after that will calculate the price for the ongoing time period. The price is calculated by the retailer using the equation:

$$S(t) = f(S_{24h}; S_{2h}; S_{com}). \quad (3)$$

where $S(t)$ – price for the ongoing price period,
 S_{24h} – electricity price in the day-ahead market,
 S_{2h} – electricity price in the intraday market,
 S_{com} – seller’s fee, which includes expenses, profits and risk of balancing electricity.

If $t = 1$, 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.

The main idea of the algorithm is that it takes into account the seller’s skills to offer consumers the best price, including his ability to forecast consumer load and carry out transactions on the power exchange. The seller’s goal is to provide consumers with as low-cost electricity as possible. If the analysis shows that the real-time electricity prices the retailer offers the consumers are not the cheapest, they can choose another electricity seller.

In [II] it was shown that in most cases the fixed tariffs were cheaper than power exchange based tariff systems. But it must be kept in mind that the former were confirmed by the Estonian Competition Authority. Today, the fixed tariff system means that the tariff is calculated on the basis of the average power exchange price to which retailer margin is added. Figures 3 and 4 show the percentage difference of household monthly electricity costs in case of the fixed tariff system and real-time tariff system. It is clearly seen from the figures that the monthly electricity costs of the 76 consumers under study depend on their load. In some cases, RTP is cheaper and in some cases, the fixed tariff is. In this study, the retailer margin is the same in both cases (0.25 cent/kWh). However, it has to be emphasized that in this comparison the consumers did not plan consumption and the comparison is made on the basis of the measured load.

Figure 3 is based on Nord Pool Spot Elspot’s Estonian prices in November 2012, when the average price was 37.49 EUR/MWh. The analysis showed that for 19 households RTP was on average 1.94% lower and for 57 households the fixed tariff was on average 3.22% lower. Figure 4 is based on Nord Pool Spot Elspot’s Estonian prices in June 2013, when the average price was 53.36 EUR/MWh and the analysis showed that for 33 households RTP was on average 3.01% lower and for 43 households the fixed tariff was on average 4.41% lower. These two periods were selected due to the great difference in average price between them. Revision of the Nord Pool Spot price history shows that electricity prices are cheaper during rainy and windy periods. In addition, during the summer planned maintenance works are conducted that are affecting the available capacity of generation units. The analysis employed fixed price packages offered by retailers and whose price was based on the average

price in the previous month. To have comparable results, comparison was made between fixed and real-time prices for the same month.

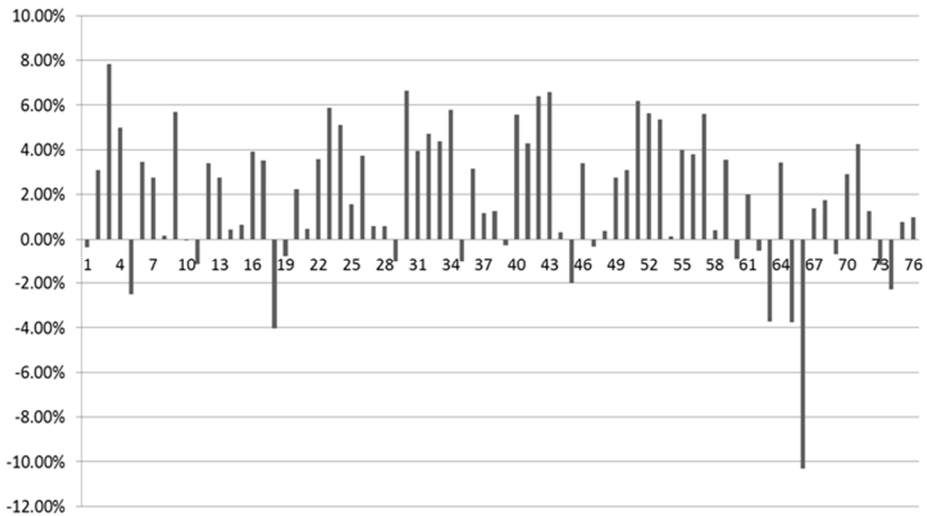


Fig. 3. The percentage difference in consumers' monthly costs in case of RTP and average power exchange price based on Nord Pool Spot Elspot's Estonian prices in November 2012.

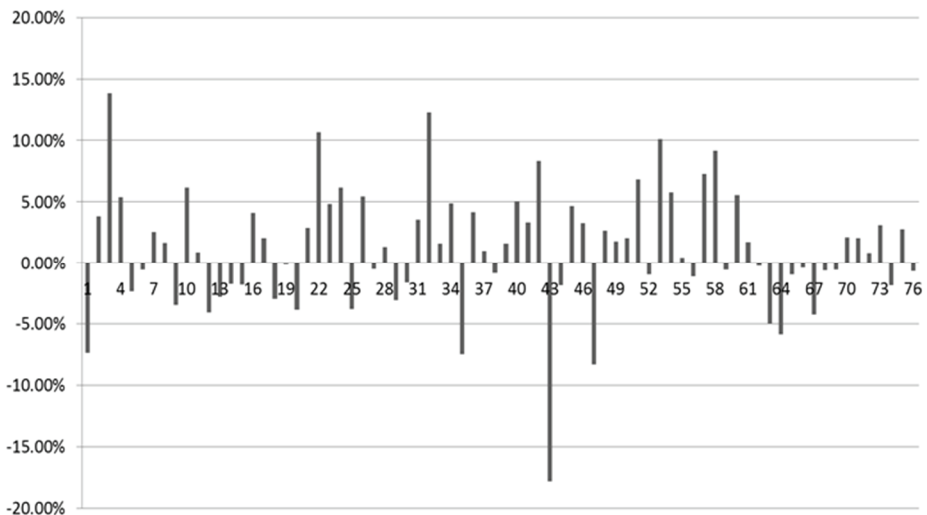


Fig. 4. The percentage difference in consumers' monthly costs in case of RTP and average power exchange price based on Nord Pool Spot Elspot's Estonian prices in June 2013.

For comparison, the analysis of closed-market prices made in [I] showed that the KODU1 tariff system proved to be the cheapest for all the 18 apartments observed. It was on average 3.5% cheaper than Elspot's Estonian area price

based RTP system. It should be noted that the analysis of the electricity market based tariff system did not include vendor's commission. It also turned out that during the observed period of time Nord Pool Spot's Estonian area price was 21.6% and Finnish area price 29.4% lower than the average electricity prices in these countries in 2011. Comparison of the price packages KINDEL and MUUTUV offered by Eesti Energia in 2013 with the regulated market tariff systems KODU1 and KODU2 shows that KINDEL was 28% more expensive than KODU1 and 18% more expensive than KODU2. When comparing the MUUTUV package to regulated tariff systems, then the former was 13.6% more expensive than KODU1 and only 4.6% more expensive than KODU2. The comparison was based on Nord Pool Spot Elspot's Estonian area prices during the period December 13–19, 2011.

2.3. Method proposed for forecasting load

In previous studies, actual consumer consumption data have not been used [9–12] and individual consumer load curves have not been analyzed. The current study is not based on theoretical equations, instead, actual consumer consumption data were employed, the measurement period being one year. Invalid measurement data being excluded, analysis of usable data needed a huge amount of work, since a one-month measurement period alone afforded over 56 000 readings.

The main idea was to develop an algorithm for RTP, considering current retail and power exchange rules. Therefore, a model to forecast load, which would also be easy to use and comprehend, was needed. The description of the proposed algorithm is given in Chapter 2.2. According to the algorithm, first the retailer has to forecast electricity consumption one-day-ahead. It is therefore necessary to have a short-term load model for forecasting such consumption.

Changes of the load can be described by a mathematical model consisting of three basic components [33, 46]:

$$l(t) = E(t) + \Gamma(t) + \Theta(t), \quad (4)$$

where $E(t)$ – mathematical expectation of the load,
 $\Gamma(t)$ – temperature-sensitive part of the load,
 $\Theta(t)$ – stochastic component of the load.

Since the data consisted of load and outside temperature values for the whole year, the regression analysis of time series method was used to demonstrate how retailers could relatively easily forecast electricity consumption. This analysis is described in Chapter 2.3.1. Being suitable for analyzing historical time series data and relatively easy to comprehend, the regression analysis of time series method was preferred to other similar approaches. Although ANN methods have been very often applied to load forecasting, it has to be kept in mind that ANN works best in nonlinear data analysis [47], and is also difficult to describe. Retailers will always be free to develop the proposed regression analysis of time series method further and combine it with other related techniques.

2.3.1. Regression analysis of time series method

Being suitable for forecasting loads on the basis of time series, the regression analysis was chosen. The analysis allows creating models in such a way that the dependencies involved are properly taken into account. For retailers the regression analysis of time series method is easy to use and they can also improve it by adding different variables.

Time series analysis is used for many purposes such as:

- budgetary analysis;
- stock market analysis;
- workload projections;
- utility studies;
- Census analysis;
- yield projections;
- economic forecasting.

For load forecasting, it is necessary to create a mathematical model to describe load. In the current thesis, the load is described as a general model:

$$l_a(t) = l_E(t, C,) + \theta(t), \quad (5)$$

where $l_a(t)$ – actual load,
 $l_E(t, C)$ – mathematical load expectation,
 $\theta(t)$ – stochastic component,
 C – temperature.

Mathematical load expectation describes regular changes in the load, such as overall growth, seasonal, intraweek and intraday periodicities. 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.

2.3.2. Use of regression analysis of time series method to forecast household electricity consumption

In this section it is shown how it is possible to achieve a reasonably high forecasting accuracy by using relatively simple forecasting models. The first objective was to determine the variable to be used as input when constructing a model. Model output, i.e. mathematical load expectation, will depend on different inputs. A mathematical model describes principal changes of load. The model considers regular changes, temperature dependency, and the stochastic nature of load. Regular changes are load, trend, sessional, weekly and daily periods; and load level on certain days (e.g., holidays) [34].

In this work, the following three variables, which are likely to influence consumption most, were chosen as inputs:

- day (weekend, working day, etc.);
- time;
- temperature.

The distinction between days and times of day is necessary as results from Figure 1 where load variations are clearly depicted.

In order to determine whether household load depends on temperature, the corresponding correlation was found. Overall, the consumption data of 72 households during 6497 hours and concurrent outside temperature values were used. Figure 5 clearly shows that there is a strong correlation between load and outside temperature. Additional related figures are given in [III] and [V].

The load-outside temperature correlation has also been analyzed previously. However, so far it has not been possible to distinguish between individual consumers and analyses have been limited merely to different consumer groups. In [48], the correlation between outside temperature and residential and commercial customer load in Taiwan was found, but no dependence between temperature and industrial customer load was established. Unfortunately, the aforementioned study gives no correlation figures.

When analyzing the load-temperature correlation in this study, a strong correlation between the electricity consumption of private houses and outdoor temperature was observed. At the same time, there was practically no correlation between apartment consumption and outdoor temperature. This is likely due to the fact that the apartment building had central heating and the weak correlation depicted in Figure 5 can be explained by daylight hours, because in Estonia a colder season means less daylight. Nevertheless, apartments were not excluded from the study. Thus, it can be concluded that mainly private houses accounted for the dependence of load on temperature established in this research. Based on Figure 5 one can also state that in Estonia, the relationship between measured temperature and load is negative, i.e. the increase in temperature leads to a decrease in consumption, and vice versa. However, depending on geographic location this relationship may also be positive, as shown in [49, 50]. This, for example, has been observed in regions with milder climatic conditions where with increasing temperature consumption also increases, and vice versa.

From Figure 1 it can be seen that the measured consumer load curve differs from the Estonian load curve. This is explained by the fact that neither industries nor businesses were involved in the study.

Also, an assumption was made that temperature and load have a linear relationship, which depends on the time of day and weekday. In addition, to establish the temperature-load relationship for holidays, different functions were found. Thus, for a total of 24 hours per day, 7 days a week and additional 24 hours per grouped public holidays in separate functions, in all 192 functions to determine load dependence on temperature were created. For the observed customers, daily load curves on the basis of time series were created, in which temperature dependence was included. Each function can be expressed as follows:

$$l_{24h}(t, d) = a(t, d) \cdot C + b(t, d), \quad (6)$$

where $l_{24h}(t, d)$ – forecast for the next 24-hour consumption that is used for making transactions in Elspot;
 $a(t, d), b(t, d)$ – parameters which depend on the time of day and weekday;
 C – temperature.

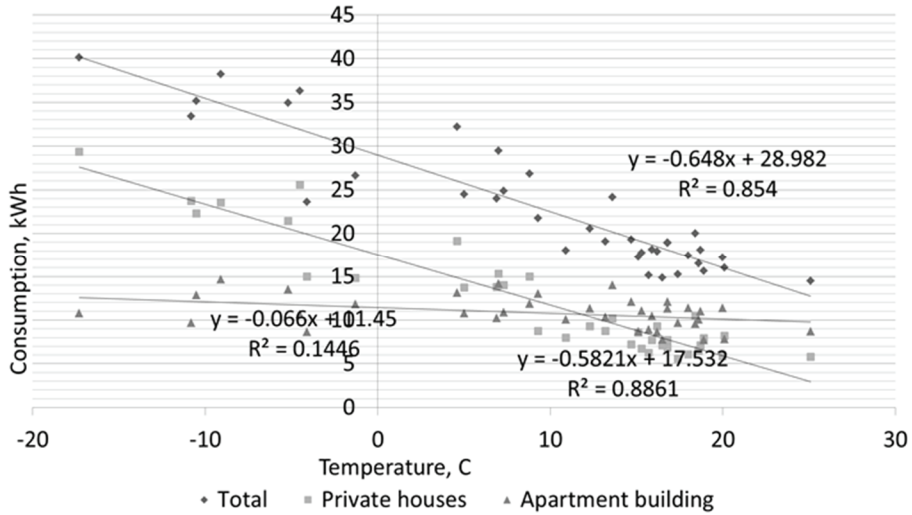


Fig. 5. Correlation between consumption and temperature on Wednesdays at 1 p.m.

To assess the accuracy of the model, SPSS software was used. The results are depicted in Figure 6. When using outside temperature as one of the inputs in the model, the accuracy on Wednesdays at 7 p.m. is 79.2% and studentized residual has rather a good distribution. The overall accuracy of the proposed methods is assessed in Chapter 2.3.4.

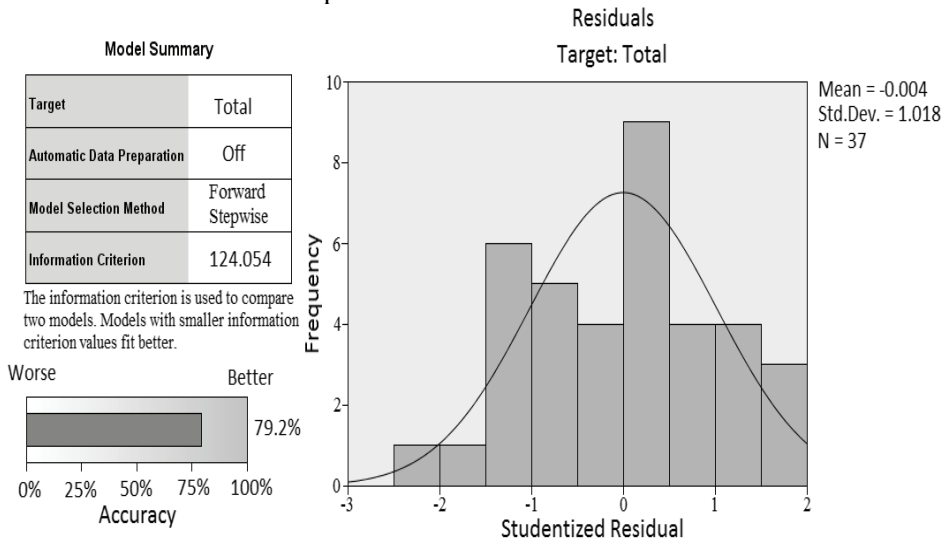


Fig. 6. SPSS model analysis of consumption- temperature dependence on Wednesdays at 7 p.m.

2.3.3. Correction of one-day-ahead forecast using the regression analysis of time series method

In this section, the results of correction of the forecast using the regression analysis of time series method are presented. According to the proposed algorithm described in Chapter 2.2, the retailer has the possibility to make a correction of the one-day-ahead forecast to minimize the difference between one-day-ahead forecasted and actual loads. Therefore, the minimization equation is given as:

$$\min \Delta l(t) = l_{24h}(t, d) - l_{2h}(t), \quad (7)$$

where $\Delta l(t)$ – difference between one-day-ahead forecasted and actual loads, kWh;

$l_{2h}(t)$ – correction of one-day-ahead forecast used for making transactions in Elbas.

Thereafter it was necessary to find a way to use recent actual load information as input and then optimize the number of hours of recent information to be used as input. The aim was to develop a straightforward function that compares the previous hours correction difference between one-day-ahead forecast and actual load. The optimization revealed that recent four-hour information gave the most accurate results. The corresponding function can be expressed as follows:

$$l_{2h}(t) = l_{24h}(t, d) + l_{24h}(t, d) \cdot \frac{\sum_{i=2}^5 \frac{l_a(t-i) - l_{24h}(t-i, d) \cdot \alpha_{t-i}}{l_{24h}(t-i, d)}}{4}, \quad (8)$$

where $l_a(t - i)$ – actual load at time t ;

α_{t-1} – coefficient that takes into account the previous hours correction difference;

i – previous hours of actual time.

It is important to prefer newer data to older values. For this purpose, the coefficient α_t was used in order to minimize the difference in two-hours-ahead correction error. In the current work, $\alpha_{t-5} = 0.4$, $\alpha_{t-4} = 0.6$, $\alpha_{t-3} = 0.8$, and $\alpha_{t-2} = 1.0$. α_t was not readjusted for every day but was calculated for the whole measurement period.

The comparison of measured consumption, one-day-ahead forecast and two-hours-ahead correction of forecast is illustrated in Figure 7. From the figure it is clear that the loads calculated using equation (4) reduce the difference between the one-day-ahead forecast and the actual measured load. In [III] it is stated that in certain situations, using equation (4) can cause a greater difference between the actual and forecasted loads. In other words, the equation reduces the error made by forecasting load one-day-ahead.

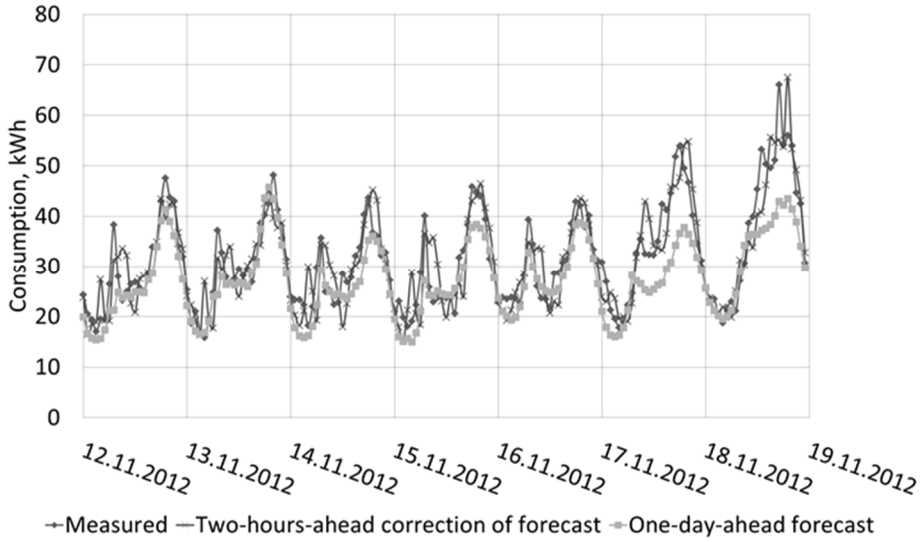


Fig. 7. Measured consumption, one-day-ahead forecast and two-hours-ahead correction of forecast during the period November 12–19, 2012.

2.3.4. Accuracy of forecasting

In this section, the results of using the regression analysis of time series method and the correction of forecast are presented. In order to evaluate the accuracy of forecasting and the proposed correction function, the mean absolute percentage error (MAPE) was used. MAPE is a measure of accuracy of a method for constructing fitted time series.

MAPE is calculated by the following equation [11, 12]:

$$MAPE = \frac{1}{N} \sum_{t=1}^N \left| \frac{[l_e(t) - l_a(t)] \cdot 100}{l(t)} \right|, \quad (9)$$

where $l_a(t)$ – actual load;

$l_e(t)$ – mathematical load expectation (in case of l_{24h} and l_{2h} , 24-hours-ahead forecast and accuracy of two-hours-ahead forecast correction, respectively, was evaluated);

N – population of the evaluation set.

In [III], MAPE was assessed. The MAPE for one-day-ahead forecast was 14.2% and for the two-hours-ahead correction of the forecast 10.7%. It was concluded that despite the relatively large MAPE of prediction, the results of the current work are reliable. It is also clear that the one-day-ahead forecast information is in agreement with real load data and the correction made two-hours-ahead reduces the error made in the one-day-ahead forecast.

2.4. Estimation of the influence of real-time pricing on smoothing the Estonian load curve

In Estonian distribution grid there are about 554 000 measuring points that have an electricity contract, and about 160 000 measuring points that have not.

Consumers with no electricity contract are consuming electricity under the generic service provided by DNO [51]. Nevertheless, most Estonian consumers are price sensitive.

From Figure 8 it can be seen that during the winter, the daily consumption peak is 1500 MW and minimum 950 MW. As seen in Figure 9, during the summer, the daily consumption peak is 900 MW and minimum 500 MW. This means that the difference between the daily peak and minimum load is relatively large. As results from Figure 10, household consumption has been approximately one-third of total consumption over the past years. Therefore, it can be assumed that household DR will not have a strong influence on smoothing the Estonian load curve. Thus, it would be necessary to offer RTP to other economic sectors as well, for instance, the industry sector.

The difference between peak load and off-peak periods could increase even more. For example, Estonian TSO, Elering, has assessed that in 2030 the percentage of electrical cars may be 10–30%, and has proposed two different scenarios [52]:

- a. managing car charging;
- b. not managing car charging.

Depending on the number of cars, the system load will increase 30–75 MW during off-peak load periods. The load will increase even more during the night, and therefore, with the addition of electric vehicles planned charging will have a smoothing effect on system load. Additional daily consumption of electricity during peak demand will increase by 2–5%. If car charging is not managed, the load during peak load hours could increase from 40 to 100 MW. [52]

In Figures 8 and 9, theoretical load curves in case of increasing use of electrical cars and whether load is managed or not, are visualized. It is assumed that if load is managed, the daily load peak will increase 5% and off-peak 10%. If load is not managed, then it is assumed that the daily load will increase 10% and off-peak 5%. Household load curve is calculated on the basis of measurements taken in Loo village in 2012 and the 30% share of household consumption in the total consumption. It is clearly seen that in case of load nonmanagement the difference between off-peak and peak load will increase.

In addition to electrical cars, managing the use of heat pumps has a great potential for increasing DR. In the beginning of 2013, heat pumps with a total capacity of 250 MW were installed by the members of the Estonian Heat Pump Association¹. These pumps are estimated to produce approximately 760 GWh of thermal energy extracted from the ground and air, using approximately 250 GWh of electricity [53]. Therefore, it can be expected that the use of electricity for heating or cooling will increase.

¹ Eesti Soojuspumba Liit

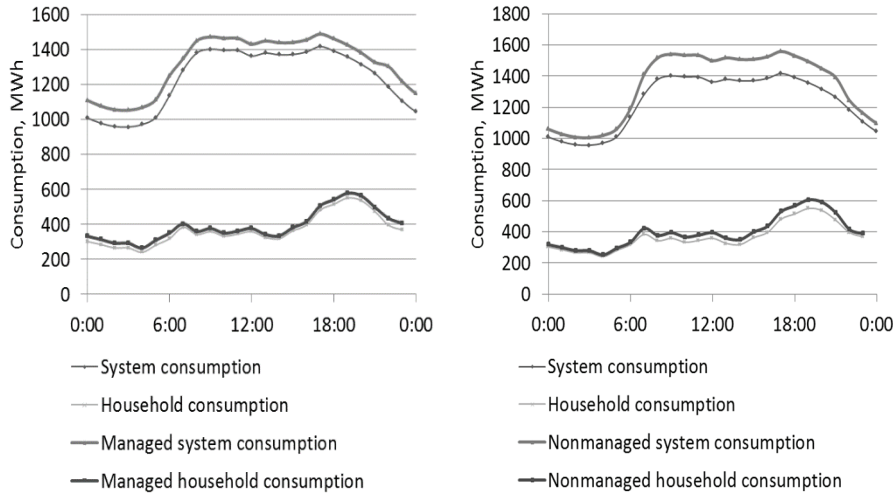


Fig. 8. Estonian electricity consumption during one day in winter in case of managed (left) and nonmanaged load (right) [54].

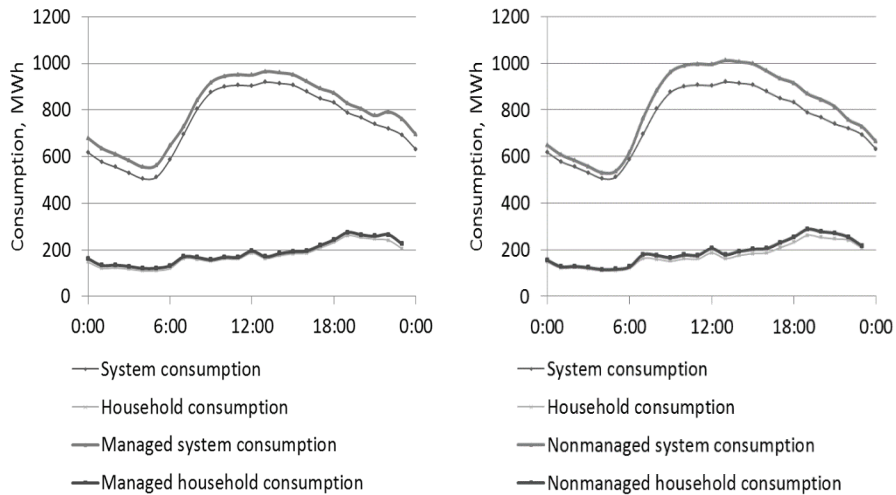


Figure 9. Estonian electricity consumption during one day in summer in case of managed (left) and nonmanaged load (right) [54].

Due to the increasing use of electrical cars and heat pumps it is possible that with a better electricity consumption management, its effect on DR will increase. Therefore, RTP can motivate consumers to plan charging electrical cars or to automate heating/cooling control. With the residential load control systems proposed in [55], processing the real-time price information by automatically managing the power usage for the households in the most preferable and economical way, DR will be more effective. Overall, enabling price responsiveness can help mitigate price spikes and market power [5]. In [56] it was concluded that when water heating is rescheduled to off-peak time,

then it leads to a relatively high financial saving. In addition to traditional devices, battery energy storage systems [57] must not be forgotten because they can be charged during off-peak hours and the electricity stored can be used during peak hours. Furthermore, there are papers that point out that electrical cars could be used as power storage units [58]. Still the power storage units are relatively expensive and other alternative DR methods are more economical. RTP is definitely an advantageous method to raise DR.

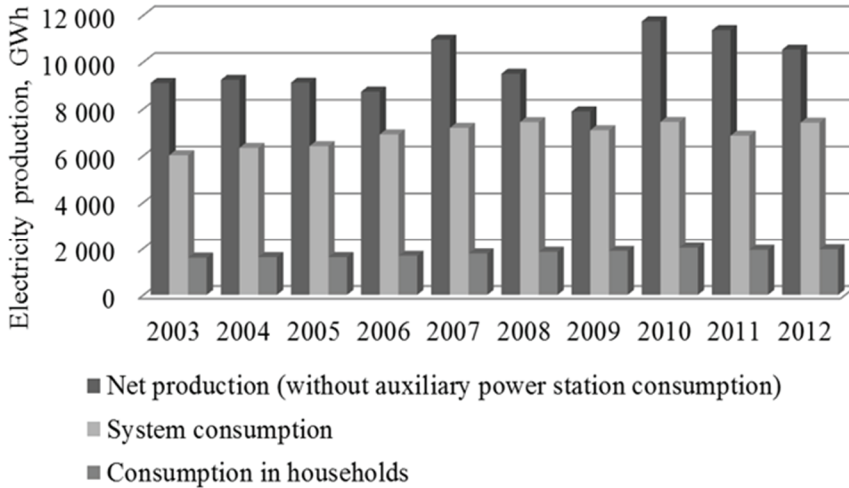


Figure 10. Estonian net production, system consumption, and consumption in households [13].

3. DISCUSSION

In the current study, the real-time tariff system was defined and an algorithm for RTP was proposed. Real-time tariff can be defined as follows: retailer charges for delivered electricity that vary hourly and are determined by power exchange prices by using the algorithm approved and verified by the regulator. Since it is not possible to calculate prices in real time, calculations have to be made according to the determined time interval. The proposed algorithm is based on current power exchange rules and it would be difficult to change the rules. The trading interval, however, could be easily changed. To protect consumers and to have retailer's credibility, it is necessary for someone to verify that the retailers trade according to the approved algorithm and these verifications can be made by the Estonian Competition Authority.

Algorithms for real-time tariff systems have also been published previously and they all have their advantages and disadvantages. For example, in [59] an algorithm that is based on utility maximization is described. [60] proposes an RTP algorithm for the electricity provider and the subscribers to compute optimal price, demand and generating capacity simultaneously. The electricity provider announces two prices of electricity in real time based on the total load demand. The provider announces the price to the residential subscribers and they announce their optimal power consumption to the provider based on the announced price. The same scenario applies to the commercial subscribers but with another price. Finally, the electricity provider announces a price to the residential subscribers and another price to the commercial subscribers [60]. These examples are theoretical algorithms which are difficult to realistically implement. Also, the use of these theoretical algorithms would mean that one control centre would be created, which would manage all the different utilities. However, it would be a step backwards and the question of how the power markets and exchanges would operate in these theoretical algorithm conditions would be unclear. The algorithm proposed in the current thesis, however, is logical and meets current power exchange rules.

In this study, the suitability of the proposed algorithm for RTP was investigated taking into account current power exchange rules and technology available. Conventional tariff systems do not raise DR, but DR is one of the key elements of smart grids. The costs of electricity generation are rising and consumers should have more possibilities to control and plan their consumption. Power saving and more sustainable household appliances and respective developments have been issues of concern/discussion for a long time. The next step would be developing real-time tariffs. This study also assessed the economic feasibility of RTP or conventional pricing packages for consumers. In [II] it was concluded that the fixed tariffs that were confirmed by the Estonian Competition Authority were in most cases more beneficial to consumers than RTP. Also, when liberated market prices were compared to theoretical RTP, then it appeared that in most cases conventional tariff systems were economically more feasible despite the fact that in the closed market situation the electricity prices were cheaper and confirmed by the Estonian Competition

Authority. Still, it has to be taken into account that in case of both studies the consumers did not plan consumption and comparison was based on measured load. In case of managing consumption and moving load partly to off-peak hours, economic savings can be greater. In addition, the development plan of TSO predicts that the use of electrical cars will increase [52]. Therefore, planning the charging time of electrical cars will definitely give additional benefits to customers.

The proposed algorithm provides retailers the opportunity to correct the one-day-ahead forecast by buying electricity from or selling it to Elbas. Unfortunately, Elbas is currently not very active in Estonia. In 2013, on average 89% of the electricity consumed in Estonian electricity system was purchased from Elspot and 92% of the electricity generated was sold to Elspot [40]. Therefore, using the proposed RTP algorithm should have a positive effect on trading on Elbas and different retailers would start using Elbas, which will increase retailers' flexibility to offer the best price.

In the current study, the possibility of using outside temperature information as input in a load forecasting model was investigated. For this purpose, the respective measurements were carried out during one year. It was found that private household load strongly correlated with outside temperature, while the opposite was observed with apartment load. Despite these findings, retailers will always be free to analyze consumer load curves and determine whether it is reasonable to use temperature as one of the inputs. This study demonstrated that it depended on consumers' habits whether the use of correlation between load and temperature as an input in short-time load forecasting was justified. In addition, when including the thermal inertia as input in forecasting the load, the accuracy decreased (data not shown). It can be assumed that just like temperature sensitivity, the thermal inertia also depends on the consumers' habits. This will need further study to improve also the forecasting method.

When using electricity for heating, a better thermal insulation of buildings will substantially decrease correlation between load and temperature. The use of electricity for heating houses depends on various factors. There are also devices which raise load-temperature relationship, like air conditioners, outdoor area heating installations, electrical cars. In the United States, residential electricity consumption survey showed that space heating and water heating contributes most to total household electricity consumption [61], but of course it depends on the geographic location. The country's geographical location lets one assume that the same applies also to Estonia.

The final issue of discussion is whether the chosen forecasting method, regression analysis of time series method, is suitable for short-term load forecasting. This method was preferred to other methods because it is relatively easy to describe, is suitable for analyzing historical time series data and is relatively straightforward. The use of ANN methods was also considered, because these methods have been very often applied to forecasting load [37, 60, 62]. In addition, the ANN models are able to learn and generalize information during each forecast, and strengthen or weaken interconnected weights that

connect the processing inputs of the model. However, these methods are difficult to describe and they work best in nonlinear data analysis. After the method selection, time, day and outside temperature were chosen as inputs. Next, the regression analysis of time series method was supplemented with the two-hours-ahead correction of the forecast made using the regression analysis, according to the proposed RTP algorithm. The MAPE for one-day-ahead forecasting was found to be 14.2% and for two-hours-ahead correction of the forecast 10.7%. When the ANN method was used for forecasting load one-day-ahead, then the MAPE was found to be from 7.09% to 11.33%, depending on the number of input variables/volume of the historical data used [63]. Despite the relatively large MAPE of prediction obtained in the current study, it can still be satisfied with the results of the current work and it is clear that the one-day-ahead forecast coincides with real load and the correction made two-hours-ahead reduces the error made by one-day-ahead forecasting. The relatively large forecasting error is mainly caused by the very small number of surveyed consumers, since the stochastic variation in the consumption of each consumer has a strong effect on the entire load curve of a set of consumers. With a greater number of consumers the resulting prediction error of the proposed method will probably be significantly reduced as also indicated by other studies. For example, when using a larger amount of power system information as input, the accuracy will increase. In [12], historical electricity load data of the ISO New England market were used and with the ANN method employed for forecasting, the MAPE varied from 0.9% to 3.87%. [45] showed that inclusion of all the available information about energy consumption on working days, weekends and national holidays improves the forecasting accuracy. Also, information gathered at 15-minute intervals seems to be more reliable than data collected at one-hour intervals. Nevertheless, in the current study a relatively high accuracy was achieved, despite the fact that only 76 households were involved, whose load was measured at one-hour intervals. Based on this work, retailers can develop the proposed forecasting method further by adding different inputs and combining it with other similar methods.

CONCLUSIONS AND FUTURE WORK

The first objective of the thesis was to propose RTP for retail market. The conventional price packages offered today to retail consumers do not mirror the actual costs of electricity production. Retailers offer price packages which involve generally only two electricity rates – daily and nightly. In this study, RTP is defined as retailer charges for delivered electricity, which vary hour by hour and are determined by power exchange prices by using an approved and verified algorithm.

In the current work, an algorithm developed for RTP based on current power exchange rules was proposed. It is necessary to work out an optimal time interval for changing the price. In this study, it was based on the power exchange trading intervals, but shorter or longer intervals could result in additional benefits. For instance, it has been found that using the 15-minute interval clearly affords higher accuracy than the one-hour interval when forecasting the load to make transactions in the one-day-ahead market.

A regression analysis of time series method was proposed for forecasting consumption one-day-ahead. The analysis showed that there was a correlation between outside temperature and household electricity consumption. Therefore, in addition to day and time, this correlation was also employed as input in forecasting. Also, an equation for correcting the one-day-ahead forecast two-hours-ahead was developed. As stated, in certain situations, using the proposed equation may lead to a greater difference between the actual and forecasted loads. Therefore, it is necessary to develop the method further to exclude the possibility when in certain situations, using the proposed equation can cause a greater difference. The greater difference means additional costs for the retailer which could mean higher retailer margin, i.e. higher electricity price for consumers. Overall, the analyses showed that using the regression analysis of time series method the electricity consumption in households forecasted one-day-ahead was sufficiently accurate. The mean absolute percentage error for one-day-ahead forecasting was 14.2% and for two-hours-ahead correction of the forecast, 10.7%. This is a very good result considering the proportion of the stochastic component in the study. With the proposed algorithm, it is possible to correct the accuracy of one-day-ahead forecast. The retailer could use the proposed method and add different variables or combine it with other forecasting methods. Thus, the results of this thesis showed that the regression analysis of time series method is accurate enough and that the proposed algorithm can be successfully applied to RTP.

The development of RTP depends on Estonia's electricity and open market policies. Furthermore, the electricity market price and investment costs of metering and communication system technologies are important factors for future developments. Since RTP involves larger communication capacities, reliability requirements and security, the need for guidelines is high as well.

The study showed that in case of RTP it is clear that consumers's monthly costs depend on their load curve. In some cases the RTP is cheaper and in some cases the fixed tariff is cheaper. Of course it has to be noted that in the present

study consumption was not managed. When consumption would have been managed, then RTP could in most situations have been cheaper than fixed tariffs.

In the current study, the potential of RTP for smoothing the load curve was analyzed. With the implementation of RTP, the overall DR will increase and consumers will have more opportunities to choose between. With the growth of distributed generation, even higher electricity price volatility is expected, which is, however, not necessarily disadvantageous. RTP shifts price risk from the utility to the customer and therefore the question of what is the optimal time of advance notice of prices emerges. In this work it is proposed that the customer should be notified about price at the beginning of the trading period. Despite the emergence of different new technologies, it can be assumed that RTP has a good prospect for smoothing the load curve. The price difference between peak and off-peak time intervals has to be great enough to motivate consumers to plan their consumption, and automated control of electricity consumption will contribute to their welfare.

In addition, the future work should focus on elaborating the approved algorithm of RTP. Although this thesis involved mainly Estonian consumers, its findings as well as the methods and models used can also be employed in other countries. Literature about RTP in the Estonian language is needed. Finally, field legislation should be renewed, i.e. the Electricity Market Act and the Grid Code have to be reviewed and necessary modifications made. In conclusion, the current research may serve as a basis for further related studies that may eventually lead to the emergence of an effective real-time charging system.

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ABSTRACT

Due to the liberalization of electricity markets, consumers have the opportunity to choose among different electricity sellers. Unfortunately, creation of the power exchange and open electricity market was not accompanied by completely new electricity packages. Current electricity packets are divided into three packages – packages depending on power exchange price, fixed-price packages and the generic service package.

The main objective of this thesis was to develop an algorithm for retail electricity sellers to provide consumers with a real-time tariff system. In addition, it was aimed to define the real-time tariff system and propose a method, which would be suitable to predict consumer load one day in advance, using the real-time pricing algorithm developed.

The real-time pricing algorithm based on current market rules was worked out and as a result, real-time tariff system was defined as retailers charges for delivered electricity that vary hour by hour and are determined by power exchange prices by using an approved and verified algorithm.

In the present work, during one-year measurement period the consumption of 76 consumers was monitored, and subsequently, consumer-specific load curves were generated. When monthly costs of monitored consumers in case of fixed and theoretical real-time tariffs were analyzed, it could not be firmly concluded that real-time pricing was economically feasible for all the consumers. Nevertheless, the analysis revealed that for those consumers whose consumption took place during system off-peak load periods, the real-time tariff system would lower monthly costs. In addition, it has to be taken into account that during the research, the consumers did not manage their consumption. This means that if costs are managed, consumers' expenses will likely decrease even more. Furthermore, the study attempted to find it out whether there was a correlation between household load and outdoor temperature. The analysis showed that even though the apartment load had no correlation with outside temperature, the private households load was tightly linked to the outside temperature and thus could be used for forecasting load.

Another aim of the study was to provide a method for forecasting load in accordance with the proposed algorithm. In this work, the time series regression method for forecasting load one day in advance was used. The SPSS software was employed to assess the accuracy of models. In addition to the day-ahead forecasting, a method to correct the one-day-ahead forecast error was proposed. The method takes into account the difference between the previous four-hour forecast and the actual load, and this information can be used to correct the one-day-ahead forecasting difference in a transaction in the intraday market. The mean absolute percentage error of one-day-ahead load forecasting was 14.2% and for the two-hours-ahead correction, 10.7%. Despite the very large content of the stochastic component, it can still be regarded as a good outcome.

As a result of this work the algorithm for and the definition of real-time tariff system which retailers could use and consumers benefit from were presented.

KOKKUVÕTE

Elektriturgude liberaliseerimisega on tarbijatel tekkinud võimalus valida erinevate elektrienergia müüjate vahel. Elektribörsi ja elektrituru loomisega ei kaasnenud aga täiesti uute elektripakettide kasutuselevõttu. Praegused elektrienergia paketid jagunevad kolmeks – börsihinnast sõltuvad paketid, fikseeritud hinnaga paketid ja üldteenuse pakett.

Käesoleva doktoritöö peamiseks eesmärgiks oli välja töötada algoritm, millega jaeturu elektrimüüjad saaksid tarbijatele pakkuda reaajas muutuvat elektrienergia paketti. Lisaks oli eesmärgiks defineerida reaalaaja tariifisüsteem ja pakkuda välja meetod, millega on võimalik prognoosida tarbijate koormust üks päev ette ning mis sobiks väljatöötatud reaalaaja elektrienergia paketi algoritmiga.

Käesolevas töös pakuti välja algoritm reaalaaja tariifi süsteemile, mis põhineb praegustel turureeglitel, ning selle tulemusena defineeriti reaalaaja tariifi süsteem kui jaemüüja poolt müüdud elektrienergia hind, mis varieerub tund-tunnilt ja on määratletud elektrituru hindadega, kasutades heakskiidetud ja verifitseeritud algoritmi.

Käesolevas töös mõõdeti ühe aasta vältel 76 tarbija elektrienergia tarbimist ning selle tagajärjel tekitati iga tarbija põhine koormusgraafik. Kui analüüsiti nende tarbijate kuukulusid fikseeritud ja teoreetilise reaalaaja tariifi korral, siis polnud võimalik ammendavalt öelda, et reaalaaja tariif on tarbijale majanduslikult otstarbekam kui fikseeritud tariif. Samas selgus analüüsi käigus, et nendele tarbijatele, kelle tarbimisest suurem osa langes süsteemi tipukoormusevälisele ajale, oli reaajas muutuva tariifisüsteemi põhjal arvutatav kuukulu siiski väiksem. Siinjuures tuleb rõhutada, et käesolevas töös ei planeerinud tarbijad oma tarbimist, mis tähendab, et koormust planeerides oleks tõenäoline mõju kulutustele veelgi suurem ja seega elektrienergia arve kuu lõikes veelgi väiksem. Lisaks uuriti käesolevas töös, kas esineb korrelatsioon majapidamise tarbimise ja välisõhu temperatuuri vahel. Analüüs näitas, et kuigi korterite tarbimise ja välisõhu temperatuuri vahel puudub korrelatsioon, siis eramajade tarbimine ja välisõhu temperatuur on omavahel tihedalt seotud ja seega sobib koormuse prognoosimiseks.

Teine töö eesmärk oli vastavalt esitatud algoritmile pakkuda välja üks võimalik koormuse prognoosimeetod. Käesolevas töös kasutati üks päev ette koormuse prognoosimiseks aegridade regressiooni meetodit. Mudelite täpsuse hindamisel kasutati ka SPSS tarkvara. Lisaks päev ette prognoosimisele pakuti töös välja ka meetod, millega oleks võimalik päev ette tehtud prognoosi viga parandada. Selleks on vaja leida eelneva nelja tunni prognoosi ja tegeliku koormuse vaheline erinevus ning leitud koormuse erinevust arvestades teha vajalikud tehingud päevasisesel turul. Koormuse prognoosimisel üks päev ette oli keskmine absoluutne protsentuaalne viga 14.2% ja kaks tundi ette prognoosi korrigeerimisel 10.7%, mida vaatamata väga suurele stohhastilise komponendi sisaldusele võib pidada heaks tulemuseks.

Käesoleva töö tulemusena töötati välja ja defineeriti algoritm, mida müüjad saavad reaalaaja tariifisüsteemi luues kasutada ja millest saavad kasu ka tarbijad.

ELULOOKIRJELDUS

1. Isikuandmed

Ees- ja perekonnanimi: Tanel Kivipõld
Sünniaeg ja -koht: 05.05.1985, Tallinn, Eesti
Kodakondsus: Eesti
E-posti aadress: tanel.kivipold@gmail.com

2. Hariduskäik

Õppeasutus (nimetus lõpetamise ajal)	Lõpetamise aeg	Haridus (eriala/kraad)
Tallinna Tehnikaülikool	2010	Elektroenergeetika, Tehnikateaduste magistrikraad
Tallinna Tehnikaülikool	2008	Elektroenergeetika, Tehnikateaduste bakalaureuse kraad
Tallinna Polütehnikum	2005	Elektriseadmed ja süsteemid, keskeriharidus

3. Keelteoskus (alg-, kesk- või kõrgtase)

Keel	Tase
Eesti keel	Emakeel
Inglise keel	Kõrgtase
Vene keel	Algtase

4. Teenistuskäik

Töötamise aeg	Tööandja nimetus	Ametikoht
04.2014 – ...	Nordecon AS	Elektritööde osakonna juhataja
09.2012 – 04.2014	Eesti Energia AS	Projektijuht
01.2010 – 09.2012	Nordecon AS	Projektijuht
07.2009 – 12.2009	Nordecon Infra AS (Nordecon AS)	Projektijuht
01.2009 – 07.2009	AS Aspi (Nordecon AS)	Elektriinsener
06.2006 – 12.2008	AS Eesti Ehitus (Nordecon AS)	Elektriinsener
05.2004 – 09.2004	Helsingin Energia	Praktikant

5. Teadustegevus, sh tunnustused ja juhendatud lõputööd

- Leping Lep10068. Aruka jaotusvõrgu teaduslikud põhimõtted ja rakendused, 2010-2011.

- Bakalaureusetöö. Kebja, R. Elektri jaeturud Euroopas, 2013.
- Bakalaureusetöö. Kondrušina, J. Euroopa avatud jaeturgude tariifisüsteemid, 2013.

6. Kaitstud lõputööd

Magistritöö, Hajatootmise potentsiaal Eestis, 2010, juhendaja professor Juhan Valtin.

7. Teadustöö põhisuunad

Elektrienergia jaotamine, elektrienergia tarbimise prognoosimine, taastuvenergia, elektri tootmine ja müümine.

CURRICULUM VITAE

1. Personal data

Name: Tanel Kivipõld

Date and place of birth: 05.05.1985, Tallinn, Estonia

E-mail address: tanel.kivipold@gmail.com

2. Education

Educational institution	Graduation year	Education (field of study/degree)
Tallinn University of Technology	2010	Master of Science in Electrical Power Engineering
Tallinn University of Technology	2008	Bachelor of Science in Electrical Power Engineering
Tallinn Polytechnic School	2005	Electrical equipment and systems, specialized secondary education

3. Language competence/skills (fluent, average, basic skills)

Language	Level
Estonian	Native language
English	Fluent
Russian	Basic skills

4. Professional employment

Period	Organization	Position
04.2014 – ...	Nordecon AS	Head of Electrical Department
09.2012 – 03.2014	Eesti Energia AS,	Project Manager
01.2010 – 09.2012	Nordecon AS	Project Manager of Electrical Work
07.2009 – 12.2009	Nordecon Infra AS (Nordecon AS)	Project Manager of Electrical Work
01.2009 – 07.2009	AS Aspi (Nordecon AS)	Electrical Engineer
06.2006 – 12.2008	AS Eesti Ehitus (Nordecon AS)	Electrical Engineer
05.2004 – 09.2004	Helsingin Energia	Trainee

5. Research activity, including honors and thesis supervised

- Contract Lep10068. Basics and Applications of Smart Grid, 2010-2011.

- Bachelor Thesis. Kebja, R. Elektri jaeturud Euroopas, 2013.
- Bachelor Thesis. Kondrušina, J. *Euroopa avatud jaeturgude tariifisüsteemid*, 2013.

6. Defended theses

Master Thesis, Potential of dispersed generation in Estonia, 2010, supervisor Prof. Juhan Valtin.

7. Main areas of scientific work/Current research topics

Electricity distribution, forecasting electricity consumption, renewable energy, electricity production and selling.

APPENDIX A – Tables and Figures

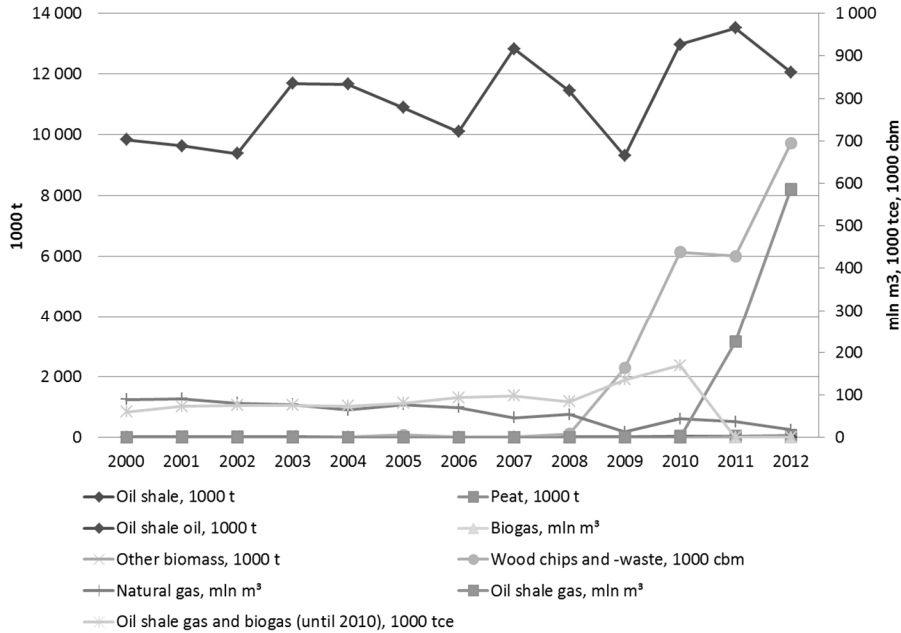


Fig. 11. Different fuels used to produce electricity in Estonia based on information in [13].

Table 1. Electricity sellers' and balance providers' proportion in the electricity consumed, % [2]

Proportion of electricity consumption	January 2014	December 2013	2013 average
Eesti Energia AS balance portfolio	60.0	71.6	71.9
Elektrum Eesti OÜ balance portfolio	14.6	9.6	10.7
Baltic Energy Services OÜ balance portfolio	10.2	9.3	9.1
incl 220 Energia OÜ percentage	2.1	2.0	1.7
incl VKG Energia percentage	1.7	2.3	1.9
incl TS Energia OÜ percentage	1.2	1.3	1.2
incl VKG Elektrivõrgud OÜ percentage	1.1	1.2	1.1
incl Sillamäe SEJ AS percentage	0.7	0.8	0.8
incl AS Loo Elekter percentage	0.3	0.2	0.2
Nordic Power Management OÜ balance portfolio	6.3	2.4	2.4
incl Imatra Elekter AS percentage	2.1	1.5	1.4

incl Eesti Gaas AS percentage	0.1	0.1	0.1
Elektrimüügi AS balance portfolio	2.0	1.9	1.4
Inter Rao Eesti OÜ balance portfolio	1.5	0.6	0.2
Elering (TSO) grid losses balance portfolio	5.4	4.6	4.3

APPENDIX B – Original publications

Paper I

Kivipõld, T., Valtin, J. Replacement of the Regulated Price of Oil Shale-Based Electricity With Open-Market Price and Real-Time Tariff System Opportunities. *Oil Shale*, Vol. 30, Issue S2, 2013, Estonia, pp. 195 - 210.

REPLACEMENT OF THE REGULATED PRICE OF OIL SHALE-BASED ELECTRICITY WITH OPEN-MARKET PRICE AND REAL-TIME TARIFF SYSTEM OPPORTUNITIES

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Abstract. *The Estonian retail electricity market opened on the 1st of January 2013. The wholesale electricity market has been operating open successfully for some time already. The liberalized electricity market creates new opportunities for consumers. From 1 January 2013, all electricity producers compete on power exchange. This means that the price of the electricity produced from oil shale is no longer regulated by the State and Narva Power Plants, like other power companies, are competing in the open electricity market.*

The liberalized electricity market and new remotely readable meters enable retail dealers to offer consumers more flexible packages. For example, a new pricing system could be developed that takes into account actual costs of electricity production at the exact time these are made.

The aim of this article is to give an overview of possibilities of real-time pricing and compare the existing tariff systems to the hourly variable pricing tariff system.

Keywords: *open retail electricity market, power exchange, tariff systems, electricity price, oil shale, real-time tariff system.*

1. Introduction

Up until 2013, the electricity price was mainly shaped by oil shale-fired power plants and the sales price limit was confirmed by the Estonian Competition Authority. The Estonian Competition Authority confirmed the price limit of electricity sold to the regulated retail market according to the Electricity and oil shale production price regulation principles drawn by the Authority on the basis of the Electricity Market Act [1].

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In Estonia, oil shale-based electricity constitutes the major part of total electricity produced and consumed, therefore it can be stated that until recently the rate of electricity to consumer depended on oil shale-based electricity generation. In 2010, for example, the overall production of electricity was 12 962 GWh and 92.3% of it was produced from oil shale [2]. In the open electricity market, the price of electricity is no longer controlled by the State, instead, it is formed on the market and power exchange. Unfortunately, the opening of the market was also accompanied by the increase of electricity price, since to home user the regulated market price was lower than the current power exchange price.

The open electricity market and remotely readable electricity meters will offer new possibilities for everyone. For decades, there have been talked over real-time tariffs. Although some researches have been made and algorithms developed offering real-time pricing system, until now there have not been appropriate technologies. No meters have been available that could measure the energy consumed at a sufficient interval, i.e. as frequently as its price changes. Technologies that could send real-time pricing information to consumers have been lacking either. But today, such a technology finally exists. Different AMI meters allow the distribution network operator [3]:

- a. to measure the consumed energy at the desired interval;
- b. to communicate with the consumer through various communication channels (power line carrier PLC, Wi-Fi, GPRS, 3G, WiMax, etc.);
- c. to switch consumer on or off the system;
- d. to limit consumer consumption;
- e. to monitor power quality;
- f. to send consumer power outage information.

By today, many developed countries around the world have deregulated their electricity markets. This is aimed at creating conditions for competition among electricity producers to ensure a fair electricity price to consumers, as well as producers. Now that the electricity market is fully open, the oil shale-based electricity is competing with that generated by other modes. In 2012, the Estonian Competition Authority set the average sales price limit of the electricity produced by Narva Power Plants to 29.4 €/MWh [4]. There were 36 power companies in the closed electricity market in Estonia and the average approved price of electricity was 32.9 €/MWh [4]. However, in 2012, the average price of electricity in the Elspot Estonian region was 39.2 €/MWh, i.e. over 19% higher than the Estonian Competition Authority approved average price.

The competitiveness of Estonian oil shale-based electricity in the open market depends on various factors, but largely on CO₂ quotas. If Narva Power Plants would purchase the required CO₂ quotas, it may raise electricity production costs even more. Oil shale-based electricity production releases much more CO₂ compared to the other methods of electricity generation. The production of 1 MWh of electricity from oil shale emits around 1.2 tons of CO₂ (the new Narva Power Plant unit releases

1.07 t/MWh and the old units 1.22–1.40 t/MWh). Whether the oil shale-based electricity is sustainable and also competitive in the open market and secures Estonia's electricity supply depends on the amount and price of the needed CO₂ quotas.

The EU energy policy's objective is to create one single electricity market. At the moment there are 13 power exchanges in the European Economic Area [5], with IPEX of Italy, EEX in Germany and Nord Pool Spot in Norway as the biggest.

In the Estonian closed electricity market conditions, the Estonian Competition Authority confirmed all electricity prices, taking into account the costs of capital, fuel, transmission, etc. In an open market the price of electricity will depend on the point on the consumption curve at which the supply and demand curves intersect. In other words, the price is derived from market equilibrium. At Nord Pool Spot, purchase orders constitute the demand curve and sale offers the supply curve (Fig. 1). The intersection of two curves generates the market price for the next hour [6]. The uniform price is the price level at the intersection of aggregated demand and supply curves and is called market clearing price. It provides a maximum trade volume, also called market-clearing trade volume [7].

Since in retail market sellers are competing with each other, the price to households is determined on competitive terms. Although in the open market households may choose between electricity packages offered by many retailers, it is unfortunate that they have to choose only between different fixed electricity price packages whose prices change monthly or even more seldom. Therefore, it is time that consumers should have the possibility

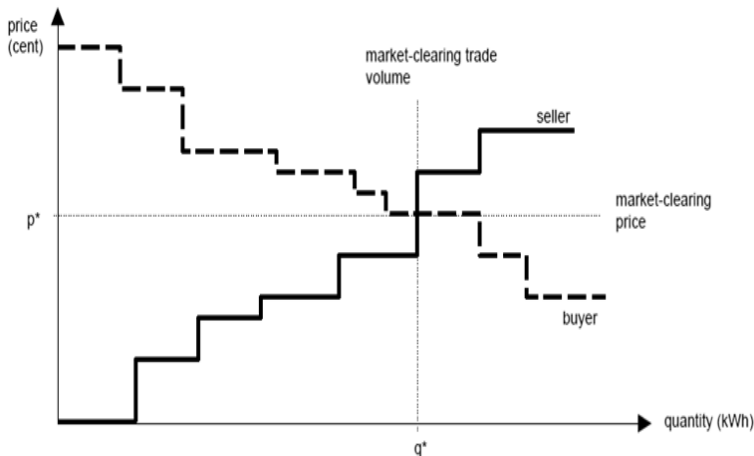


Fig. 1. Aggregated supply and demand curves [7].

to take a real-time price packet, which reflects the current market price and costs of electricity generation.

At the moment, price packages offered to consumers do not mirror actual costs of electricity production. Retailers offer price packages which involve only two rates – daily and nightly. However, this two-tariff system does not motivate consumers enough to plan consumption. Thus, it can be said that the tariffs currently offered are not attractive enough to control consumption. It is important to offer price packages which take into account the network situation and make consumer shift consumption away from peak load. Therefore, to achieve a better demand response it is important to offer more daily rate price packages, or a real-time pricing package.

Eesti Energia AS had in 2012 different price packages – KODU1, KODU2, KODU3, KODU4 and a heating package; it was also possible to choose green energy. Users having the main fuse over 63A had the possibility to select between six different price packages and it was also possible to select green energy. Nevertheless, most consumers are primarily interested in price, followed by origin of electricity, and manufacturer or seller.

In Finland, the Vatenfall energy company offers consumers a price package whose price changes according to the electricity exchange price (Nord Pool Spot, Norway). Unfortunately, the average price for the preceding month is adjusted only once a month. Besides, 3.04 €/month and commission fee of 0.25 € cents/kWh are added. Such an arrangement is actually quite similar to that of the proposed real-time pricing system. The price depends on the exchange price, changing at certain intervals, and the seller takes a fixed commission fee. However, the interval is too long and the price does not entail the production costs at the moment the energy is consumed.

2. Description and objectives of the retail electricity market

Electricity tariffs are not just there, so the seller could benefit from the goods (electricity) sold. Different tariffs could help achieve the desired goals. The main objectives the retail market tariff systems will help achieve are:

- a. reducing consumer electricity costs;
- b. motivating consumer to regulate consumption;
- c. educating consumer;
- d. increasing consumer electricity usage efficiency;
- e. increasing consumer demand response;
- f. approximating load curve;
- g. limiting peak load and decreasing load minimum;
- h. reducing balancing energy storage costs;
- i. increasing integration of wind and solar power.

In Estonia, over 90% of electricity is produced from oil shale. Unfortunately, it is difficult to regulate power production in Narva Power Plants.

Thus, it is vital to adjust the load curve and it is most likely achieved through the price of electricity. For instance, electricity at night should be considerably cheaper to motivate consumers to move consumption on the nighttime.

The wholesale and retail electricity markets have been open for some time and work without problems. Since April 1, 2010, an open consumer has had the right and obligation to choose his own electricity seller. An open consumer was a consumer that used at least 2 GWh of electricity a year at consumption sites through one or more connection points. Until 2013, open consumers formed about 30% of Estonia's electricity consumption [8]. From 1 January 2013, all consumers are open and purchase electricity at the liberalized electricity market, which in turn should boost an open retail market.

Estonia was until 2013 undergoing a period of transition from the closed regulated market to the open retail electricity market. So, users that were not open consumers had to buy electricity from their network operator and had no right to change the seller. In the closed retail market, the biggest market share carrier was Eesti Energia AS with 87% in 2009 [9]. In the regulated market, the price was always approved by the Estonian Competition Authority, depending on the costs of oil shale mining, electricity generation, transmission, distribution and sale. In 2010, household consumption accounted for 27% of total consumption and despite increasing energy prices, since 2006 electricity consumption in Estonia has been growing.

The open market consists of many different parties, like end-users, producers, traders, brokers, regulators [6]. Also, there are a transmission system operator (TSO), a distribution system operator (DSO) and a market operator.

There are about 600 000 households in the Estonian retail electricity market, most of them being price sensitive. In addition, there are approximately 100 000 commercial users. Most consumers make no distinction between kW and kWh and they purchase comfort (lighting, heat, etc.). It is important to offer consumers as clear and transparent packages as possible. All consumers should understand which elements contribute to the electricity price. In addition to households, there are bigger consumers (business customers) in the retail market, with consumption >10 MWh. Thus, the sellers should provide electricity to various customers, offering the most suitable and cheapest tariff packages. The sellers should also differentiate between domestic and commercial users. Domestic users include apartments, apartment buildings, detached houses, smart-homes, etc.

Similarly to the closed market electricity price, the price in the open retail market also forms through Formula 1. The only difference is that in the open retail market the price is shaped on competitive terms and is not approved by the Estonian Competition Authority. Grid service (transmission and distribution) is a natural monopoly whose tariffs will be continuously approved by the Estonian Competition Authority.

One of the bases of retail market is remote metering and a well-operating information system. However, a well-working retail market can only be shaped through competition. Thus, many sellers need to find their way to the retail market. Table 1 presents different possible retail-market tariff packages, their description and target groups.

Table 1. Possible tariff systems in open electricity market

Price package	Description	Target group
Fixed-price tariff system	The seller offers consumers a traditional tariff system at a fixed electricity price. It may also include different daily and nightly tariffs, for example, KODU1, KODU2, etc., packages that were offered by Eesti Energia AS in closed electricity market. The agreed rates apply for an agreed period – a year or longer.	Consumers who are accustomed to conventional tariff systems. They are not interested in controlling/planning consumption, or this is not possible. Also consumers who want to plan expenses.
Power exchange price dependent	The seller offers consumers an electricity price that depends on the average power exchange price for the previous day, week or month. It may also include daily and nightly tariffs. Electricity price applies for a calculated period.	Customers who are accustomed to traditional tariff systems. They are not interested in controlling/planning consumption, or this is not possible. At the same time, they are willing to sense the exchange price volatility. It is expected that the price is the lowest in summer and the highest in winter.
Real-time variable electricity price	The seller offers consumers electricity prices according to the power exchange prices and the trading period. Fees are added to the exchange prices.	Customers who are able and who want to regulate consumption. The main target group could be smart-home owners.

The yearly sales-based income of an electricity retailer is calculated by the formula:

$$S_{\Sigma} = \sum_{k=1}^n S_{kj}(T), \quad (1)$$

where S_{Σ} is the retailer income;
 S_{kj} is the income from one consumer;
 T is the time period;
 n is the number of consumers;
 j is the number of tariffs.

Renewable energy charge is calculated by Elering AS in accordance with the Electricity Market Act [1] and approved methodology. Elering AS is the Estonian transmission system operator (TSO) and publishes next calendar year's renewable charge every 1st of December. The charge is calculated on the basis of evaluations of the next year's subsidiaries for renewable energy, and consumed network service. Renewable energy charge is meant to

support those who generate electricity from renewable energy sources or use efficient cogeneration regime [1].

Electricity excise duty and value added tax (VAT) are decided by the parliament in accordance with the Alcohol, Tobacco and Fuel Excise Act [10].

Electricity bill may be calculated differently according to Table 1:

1. Fixed basic tariff:

$$S_{k1} = S_{E1} \cdot W, \quad (2)$$

where S_{E1} is the electricity tariff, €/kWh;

W is the electricity consumption, kWh.

2. Two fixed tariffs (daily and nightly):

$$S_{k2} = S_{E21} \cdot W_1 + S_{E22} \cdot W_2, \quad (3)$$

where S_{E21} and S_{E22} are electricity tariffs, €/kWh;

W_1 and W_2 are amounts of electricity consumed, kWh.

3. Tariff based on the average power exchange price for the previous period:

$$S_{k3} = S_{E_{t-1}} \cdot W_t, \quad (4)$$

where $S_{E_{t-1}}$ is the average exchange price for the previous period (day, week, month, year, etc.), €/kWh;

W_t is the electricity consumption during the period, kWh.

4. Real-time pricing system:

$$S_{k4} = S_{E_{t+1}} \cdot W_t, \quad (5)$$

where $S_{\text{consumer},t+1}$ is the price for the next period (15, 30, 60 minutes), notified at the beginning of the next period and which applies during the next period, €/kWh;

W_t is the electricity consumption during the period, kWh.

3. Real-time pricing system

The proposed real-time pricing system is a system that calculates the electricity price to consumer and sends him the respective information at the beginning of each time period. The interval may be 15 minutes, one hour or any of the currently suitable electricity market trading periods. The consumer price changes in real time and applies during the agreed interval. The price of electricity should reflect the network situation, i.e. availability of wind power, system load, generating capacity, temperature, etc.

For end-user the volatility of electricity price will remain a concern. Most consumers are accustomed to fixed prices and know how to plan

expenditures. But when electricity price fluctuates within a large range a day, expenditure planning will be much more complicated. The real-time tariff system could effectively help achieve objectives considered in the chapter Description and objectives of the retail electricity market.

According to the current order in the 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 seller has to make consumption prognosis one hour ahead and buy the necessary amount of electric power on the intraday market (Elbas) if needed. This means that one hour before delivery (real-time), the seller has to perform the last transaction.

Elspot is a day-ahead market. 12:00 central European time (CET) is the time of market closure for bids with the delivery for the next day. Simply put, the price is set at the point on the consumption curve at which the selling and buying price curves intersect. The price is typically announced to the market between 12:30 and 12:45 CET with a 3-minute warning, after that trades are settled. From 00:00 CET the next day, contracts are physically delivered hour by hour according to the contracts entered into. Elbas is a continuous intraday market and trading takes place every day around the clock until one hour before delivery [11].

At the moment in Estonia, the balancing energy prices and amounts are calculated on the second business day by Elering. Elering provides transmission services for producers, distribution networks and corporate consumers in Estonia. In addition, Elering provides the balancing service for balance responsible parties. Therefore the seller who wants to offer consumers the tariff system whose electricity price changes in real time has to predict balancing energy prices to calculate the price to households. The prediction of balancing energy prices clearly bears a risk for the seller and is therefore included in the seller fee.

Thus, the energy price calculated by the retailer consists of three components:

$$S_{E,t+1} = S_{t,elspot} + S_{t,elbas} + S_{commission} \quad (6)$$

where $S_{t,elspot}$ is Elspot's electricity price;
 $S_{t,elbas}$ is Elbas' electricity price;
 $S_{commission}$ is the seller fee, which includes the seller's expenses, profits and risk of balancing energy.

So, theoretically, the retailer needs 25 different models for load forecasting, considering the present organization of the electricity market. Therefore, if the trading period is one hour, then one day needs 24 models. If the trading period is shorter than one hour, even more models would be needed.

A seller for Elspot prognosticates consumer consumption in his portfolio by Formula 7 and, based on these predictions, makes necessary transactions in Elspot:

$$P_{t,\text{cons,elspot}} = f(x_1; x_2 \dots x_n), \quad (7)$$

where $P_{t,\text{cons,elspot}}$ is the predicted consumer consumption for each next day trading period;

t is the trading period (24 periods in Elspot);

$x_1; x_2 \dots x_n$ are factors that influence consumption (time, temperature, electricity price, etc.).

Thus, the price based on Elspot will be calculated by the formula:

$$S_{t,\text{elspot}} = f(P_{\text{dem}}; P_{\text{sup}}), \quad (8)$$

where P_{dem} is the power demand;

P_{sup} is the power supply.

In addition, there is another model to predict the intraday load to be employed for trading in Elbas:

$$P_{t,\text{cons,elbas}} = f(x_1; x_2 \dots x_n) - P_{t,\text{cons,elspot}}, \quad (9)$$

where $P_{t,\text{cons,elbas}}$ is the required power from Elbas;

$x_1; x_2 \dots x_n$ are factors that influence consumption (time, temperature, electricity price, etc.); here the factors are adjusted during the forecast;

$f(x_1; x_2 \dots x_n)$ is the predicted load for the next hour.

When $f(x_1; x_2 \dots x_n) = P_{t,\text{cons,elspot}}$, the prognosis is the same as the predicted load for the next hour. Therefore, an additional transaction will not be necessary.

The price based on Elbas will be calculated by the formula:

$$S_{t,\text{elbas}} = f(P_{\text{dem}}; P_{\text{sup}}). \quad (10)$$

Electricity price calculation and consumer notification should therefore be in accordance with the algorithm shown in Figure 2. The algorithm starts with checking the time, i.e. checking the next trading period. On the previous day, the seller has carried out deals in the Elspot market. So, the seller knows how much power he has bought from Elspot for the next trading period and at which price. Then the seller determines the current consumption and forecasts consumer consumption in his portfolio for the next trading period. Next, the seller examines whether the amount of power purchased from Elspot is sufficient. If there is enough power, then time is checked and if needed, the seller re-forecasts and performs an additional control. If the amount of power is not sufficient, the seller will make an additional transaction in the Elbas market, check the time again and if needed, re-forecast and perform an additional control. If $t = i-1$, Elbas is closed for the next hour trading period. The seller checks consumption until $t = i$. If $t = i$, the next trading period has begun and the seller must notify consumers of the ongoing period's electricity price. After the consumers have been notified, the seller can start calculating the price for the next period.

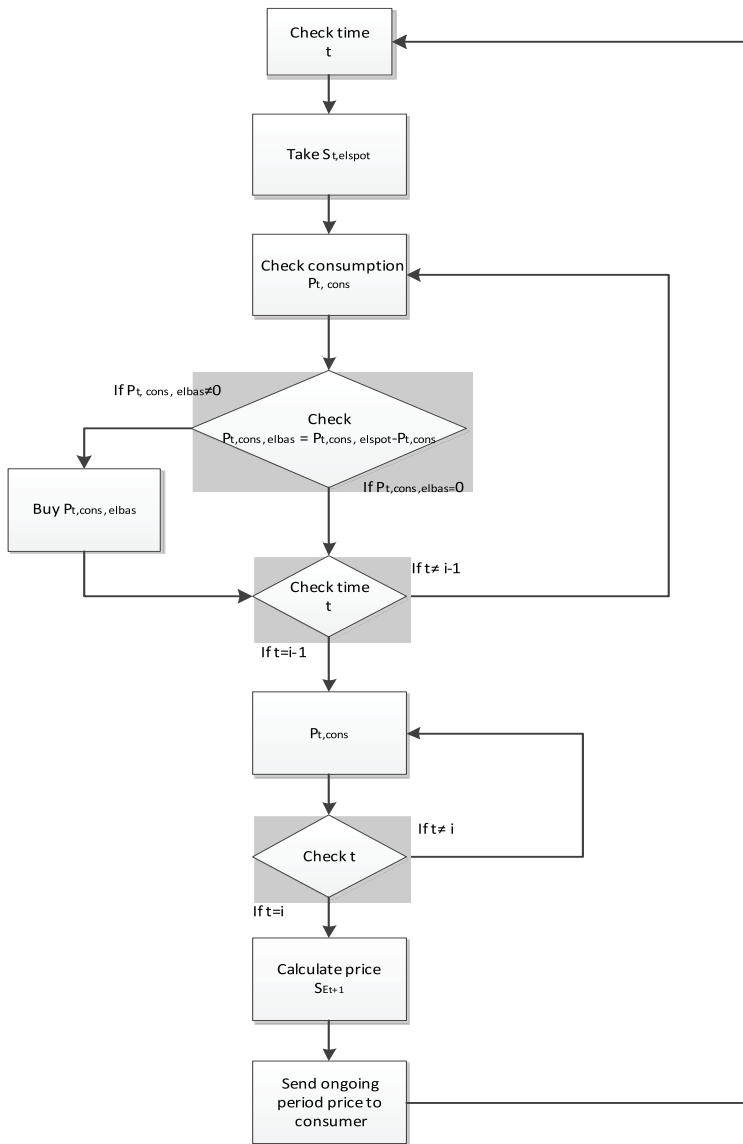


Fig. 2. Algorithm for calculating the electricity price and notifying the consumer.

With that kind of system, the price will depend on the seller's skills, i.e. his ability to forecast consumer load and carry out transactions on the power exchange. The seller's goal is to provide as low-cost electricity to consumers as possible since concurrently consumers are interested in sellers who provide the cheapest electricity. If in a consumer's opinion the seller does not offer the lowest real-time electricity price, he can choose another seller on the retail market.

4. Apartment building consumption analysis

During the period December 13–19, 2011, electricity consumption by an apartment building with 15 apartments was measured (Fig. 3). The purpose was to compare tariffs valid for the analyzed period to the tariffs of the pricing system which change on the basis of the power exchange price. Readings were taken every hour, using remotely accessed single-phase electricity meters NP 515.23D – 1E1ALNI (ADD GRUP, Moldova). This particular apartment building was a stone house with central heating, the apartments also had a furnace or fireplace, and an oven. The main fuse of one apartment was 25 A.

The aim was to create consumer load curves and determine whether the tariff system based on the market price would be more consumer friendly than the KODU1 and KODU2 tariff systems that were offered, and the price packages KINDEL and MUUTUV currently offered by Eesti Energia AS.

As expected, apartment consumption varied and was quite random. Therefore, exact load curve schedules for workdays or weekends could not be generalized. However, it may be pointed out that on workdays, consumption rose from 1 pm to 3 pm, reaching maximum, and fell from 7 pm to 9 pm. On weekends, consumption increased between 7 am and 9 am and dropped between 6 pm and 7 pm. Since the period of measurements was relatively short, it would be necessary to monitor consumers during a longer period of time to determine their consumption habits and obtain a more detailed load curve. Figure 3 gives a good overview of how random household consumption was during the day. Figure 4 shows power consumption and power exchange prices during the period December 13–19, 2011.

The load curve for the apartment building monitored was quite similar to the Estonian load curve, consumption peaks fell on higher price rate periods. Also, it became obvious that due to the timing of the main electricity consumption, the electricity bills of individual consumers tend not to decrease if the electricity price is based on the market price.

For all apartments, the KODU1 tariff system proved to be the cheapest. It was on average 3.5% cheaper than Elspot's Estonian area price based real-time pricing system and 4.4% cheaper than the Finnish area price based real-time pricing system. The KODU2 tariff system was more expensive than KODU1 for all apartments. However, prices of the Estonian and Finnish area price-based real-time systems were lower than the KODU2 tariff system

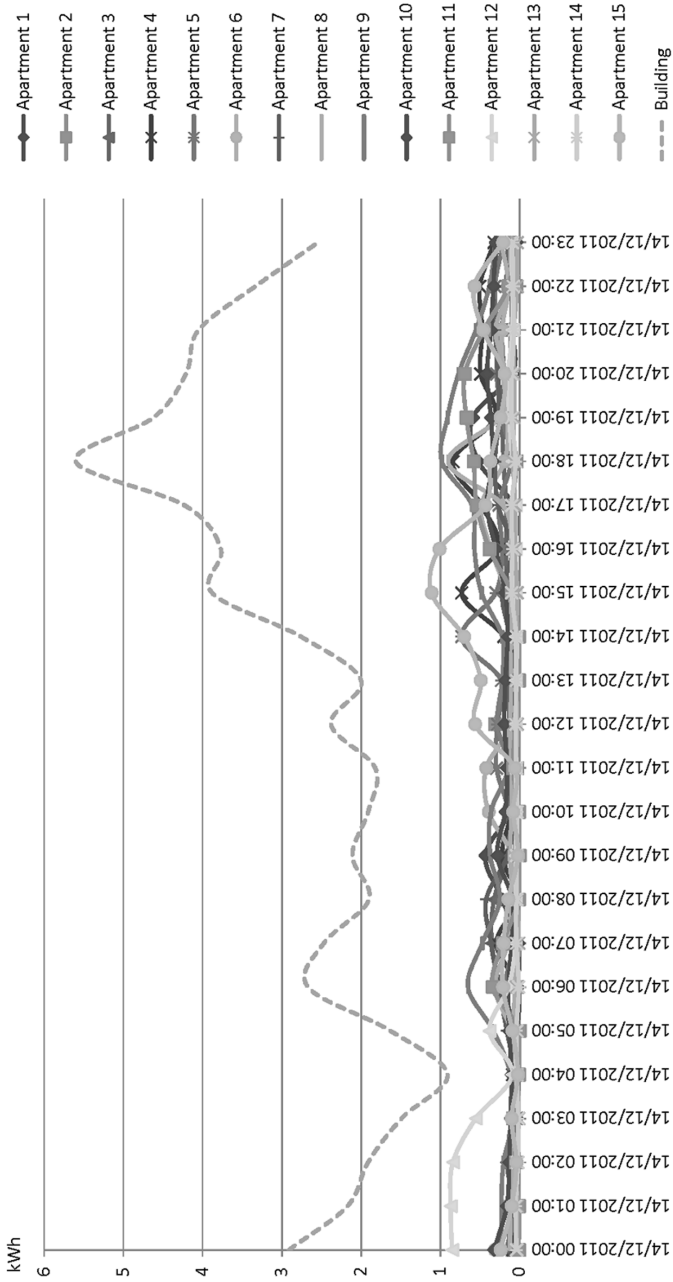


Fig. 3. Consumption by apartment building and individual apartments during one day.

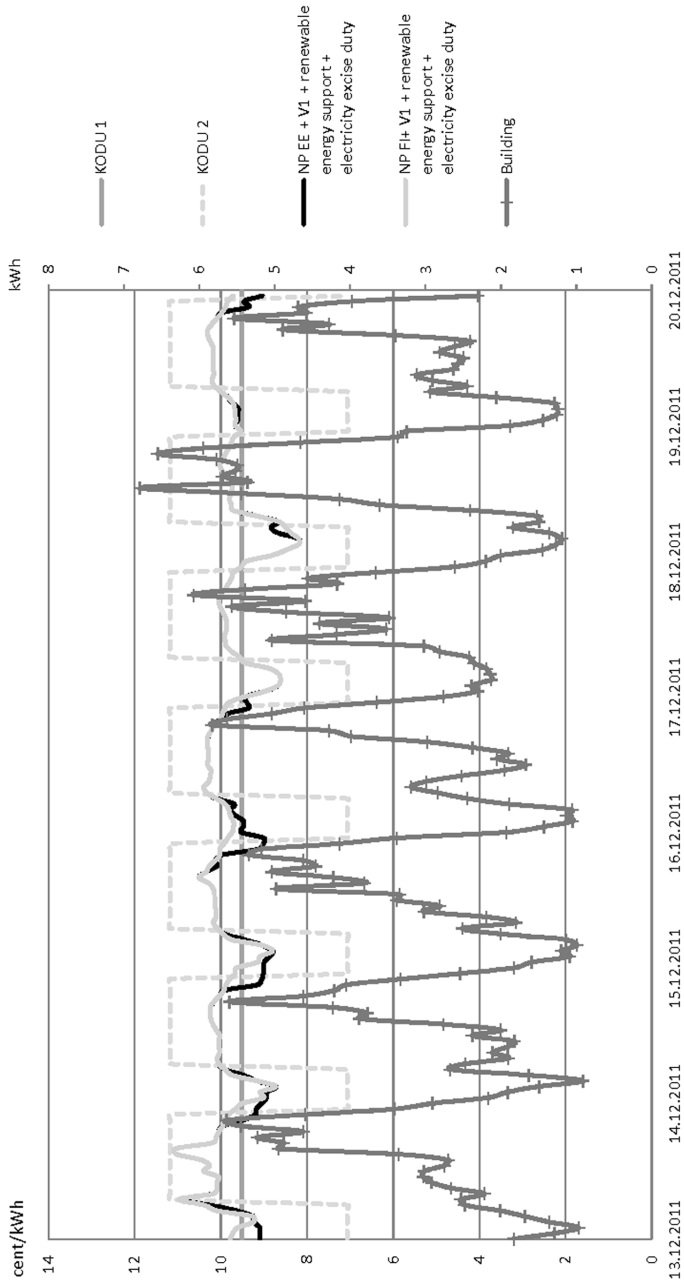


Fig. 4. Apartment consumption and electricity price, December 13–19, 2011.

price, by 4.7 and 3.9%, respectively. It should be noted that the analysis of the electricity market based tariff system did not include vendor's commission. Considering the vendor's commission, the market based pricing system would be even more expensive than KODU1 and may even surpass KODU2. It also turned out that during the observed period of time Nord Pool's Estonian area price was 21.6% and Finnish area price 29.4% lower than their average prices in 2011.

Comparison of the price packages KINDEL and MUUTUV offered by Eesti Energia in 2013 to regulated market tariff systems KODU1 and KODU2 shows that KINDEL is 28% more expensive than KODU1 and 18% more expensive than KODU2. When comparing MUUTUV to regulated tariff systems, then MUUTUV is 13.6% more expensive than KODU1 and only 4.6% more expensive than KODU2. The comparison for the MUUTUV package was made on the basis of NordPool's Estonian area prices during the period December 13–19, 2011.

When moving the measured load curves to March 1–7, 2011 (during this period Nord Pool's Estonian and Finnish area prices were higher than the average electricity price in these regions, by 22.4 and 25.9%, respectively), KODU1 expectedly turns out to be the cheapest; Nord Pool's Estonian area price-based real-time pricing system is 24.2% and Finnish area price based real-time pricing system 32.5% more expensive. Also, compared to the KODU2 package the Nord Pool Estonian area price based real-time pricing system is 14.3% and the Finnish area price-based real-time pricing system 22.1% more expensive. However, once again it should be noted that the price based on the power exchange price does not take into account the seller's fees.

5. Conclusions

1. Currently the price packages offered to consumers do not reflect actual electricity production costs. It is important to offer price packages which take into account the network situation and make consumer move consumption away from peak load and fulfill minimum load. Therefore, to achieve a better demand response it is important to offer more daily rate price packages, or a real-time pricing package. The opening of the electricity market and application of remotely readable meters allow sellers to offer tariff systems whose electricity price will change hourly according to the power exchange price.
2. The apartment building consumption analysis showed that the electricity price based on the power exchange's hourly changing price may at times be lower than the price of regulated market's electricity price packages. For example, during the period December 13–19, 2011 NordPool's Estonian area price was 21.6% and Finnish area price 29.4% cheaper than their average prices in 2011. During the period in question, for all

apartments the KODU1 tariff system proved to be the cheapest, and the KODU2 tariff system was more expensive than KODU1 for all of them. However, the prices of Estonian and Finnish area price-based real-time systems were lower than that of the KODU2 tariff system. It should be noted that by analyzing the electricity market based tariff system vendor's commission was not included. However, considering vendor's commission, the market based pricing system would be even more expensive than KODU1 and may even surpass KODU2. It should be taken into account that KODU1 and KODU2 packages were based on the regulated electricity price. However, when comparing the currently offered price packages KINDEL and MUUTUV to the previous tariff systems of Eesti Energia AS, it appears that current price packages are up to 28% more expensive than price packages based on the regulated electricity price. Considering the appreciation of electricity in the open market, the energy price based on the hourly changing power exchange price will at times be lower than the price of fixed-price packages in the open retail market.

3. The electricity price on the power exchange is volatile and it is impossible to forecast the next year's electricity price since it depends on many different factors. It is clear that the intraday exchange market price fluctuates and during some periods of time the prices may be lower than regulated market tariffs and in other periods, higher. This means that the real-time tariff system will enable customers to regulate consumption in order to keep their electricity costs as low as possible.

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Paper II

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Overview of Intraday Variable Tariff System

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Abstract— The Estonian retail electricity market is opening on the 1st of January 2013. Remotely readable meters will be installed by the end of 2016. The liberalized electricity market creates new opportunities for sellers and consumers. Sellers can offer consumers more flexible pricing packages. For example, a new pricing system could be developed that takes actual electricity production costs into account at the exact time they are done. The aim of this article is to give an overview of the current situation in the electricity market and its future possibilities, like intraday variable pricing system, based on Estonian example. An overview is given about research and development in the particular field, and future studies by the author.

I. INTRODUCTION

The sales price limit of electricity sold to the regulated retail market so far has been confirmed by the Estonian Competition Authority (ECA) according to the Electricity and oil shale production price regulation principles drawn by the ECA on the basis of the Electricity Market Act (*Elektrituruseadus RT I 2003, 25, 153 (ES)*).

From the 1st of January 2013, however, all the customers are obligated to purchase electricity from the open electricity market. Unfortunately the opening of the retail market will also be accompanied by the increase of the electricity price, since for home users the regulated market price is currently cheaper than the power exchange price. The average price of electricity in Elspot's Estonian region in 2011 was 43,3 €/MWh, i.e. over 31% more expensive than the average price approved by the ECA. [1] [2]

In Estonia, new remotely readable meters are going to be installed by the end of 2017. In an open retail market, remotely readable meters will give rise to many innovative possibilities, for example consumed energy can be measured within a desired interval or consumers can be switched on or off. [3] Although there has been talk about real-time tariffs for decades and some researches and algorithms have been made and offered for real-time pricing systems, currently, no one offers intraday (hourly) variable price packages.

II. TARIFFS IN ESTONIA AFTER MARKET OPENING IN JANUARY 2013

At the moment, the Estonian retail market has only six electricity sellers:

1. Eesti Energia AS
2. 220 Energia OÜ
3. Imatra Elekter AS
4. VKG Elektrivõrgud OÜ
5. Elektrum Eesti OÜ
6. Elektrimüügi AS

Unfortunately, there are no signs of different approaches for the pricing systems. All electricity sellers are basically offering the same pricing systems for home users with only minor differences. It is possible to group them as:

- a. Fixed single tariff price, monthly fee may be added;
- b. Fixed two-tariff (day and night) price, monthly fee may be added;
- c. Price based on the monthly average exchange price.

Fixed single tariff and two-tariff pricing systems are suitable for consumers who are accustomed to conventional tariff systems. These customers are not interested in consumption controlling/planning or it is not possible for them. Also, fixed pricing systems are intended for consumers who want to plan their expenses.

Price based on the monthly average power exchange price is meant for consumers, who are accustomed to traditional tariff systems. Although they are not interested in consumption controlling/planning or lack this kind of possibility, they are still willing to sense the exchange price volatility. It is expected that this price is the cheapest during summer and the most expensive during winter.

The author is recognizing an additional target group of electricity consumers that has been excluded so far. This group includes consumers, who are able and who want to manage their electricity consumption. These consumers are smart home owners or in other words smarter consumers.

Since remotely readable meters are going to be installed in Estonia, it is necessary to work out algorithms and methods so the electricity sellers could offer their consumers packages where the price would be changing on a hourly basis. In order to offer the cheapest price for the consumers, the sellers would have to be able to forecast the consumption as precisely as possible.

A real-time price package is a part of smart grids and could for example help to achieve the following goals:

- a. Reduction of consumer electricity costs;
- b. Motivation of consumers to manage consumption;
- c. Increase of consumer electricity usage efficiency;
- d. Increase of consumer demand response;
- e. Approximation of load curve;
- f. Limitation of peak load and smaller load minimum;
- g. Reduction of balancing energy storage costs;
- h. Increase of wind and solar power integration.

III. FORECASTING THE LOAD

There have been a lot of ideas how to predict the load. Forecasting of the load is mostly based on statistical analysis that entails past consumption, separating the standard days, hours, holidays, weekends etc. and at the same time linking the past statistics with a parameter characterizing the current situation, for example weather (wind, temperature etc).

There are a lot of studies on short-term load forecasting and they may be classified as follows [4]:

- a. Regression models
- b. Kalman filtering
- c. Box & Jenkins models

- d. Expert systems
- e. Fuzzy inference
- f. Artificial neural network (ANN)
- g. Chaos time series analysis

In Fig. 1, the dependence of the consumption of ten private residences on the outdoor temperature during the period January 31st - February 4th of 2012 measured at 7:00 AM is shown. As it seems, there is a strong correlation between temperature and consumption. Of course it is necessary to take into account that these are private residences that have no district heating, so the dependence could be affected by using electricity for heating. It is necessary to analyze the dependence more thoroughly and to engage more consumers into the study. Also, it is necessary to conduct this study for a longer period of time and in different temperatures.

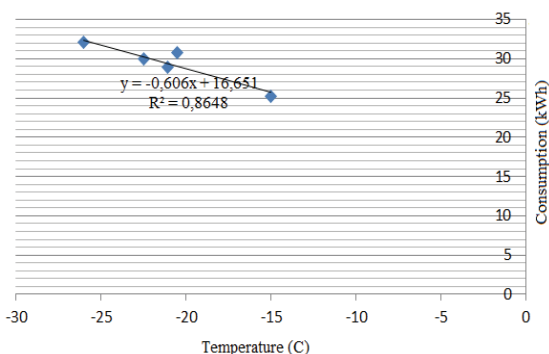


Fig. 1. The dependence of consumption of ten private residences on outdoor temperature during 5 work-days (from January 31st until February 4th 2012) measured at 7:00 AM.

IV. FUTURE STUDIES

The author will soon publish an article where a suitable algorithm for calculating the electricity price on an hourly basis is proposed.

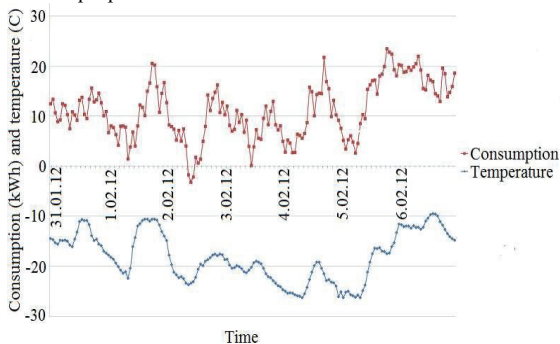


Fig. 2. Consumption of the private residences and outdoor temperatures during the period January 31st - February 6th of 2012.

The author's ongoing studies include a more in-depth analysis of the dependence of consumption and weather, the main focus being on model studies for correlation and regression analysis. These studies will help build a model for forecasting electricity demand on short or medium time scales and shaping electricity price for the consumer. In Fig. 2, where consumption of the apartment building and outdoor temperatures is shown, a correlation between the electricity demand and outdoor temperature can be seen. The main aim is to thoroughly analyze one-year consumption of various private residences and an apartment building and based on the gathered information propose a base model suitable for Estonian electricity sellers to forecast load.

V. CONCLUSIONS

The paper has given a brief overview on the situation of the open electricity market in Estonia and discussed the importance and complexity of forecasting electricity demand on short or medium time scales. In addition to the author's soon to be published algorithms for electricity price calculation in case of hourly variable pricing systems, this paper shortly introduced author's ongoing studies in the field of forecasting an electricity demand model. Once completed, these studies will give vital data on algorithms and load forecasting models which in the future will help construct a real time pricing system. A real time pricing system will be able to take actual electricity production costs into account and therefore undoubtedly form an important part in the development of smart grid projects.

ACKNOWLEDGEMENTS

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Paper III

Kivipõld, T., Valtin, J. Regression Analysis of Time Series for Forecasting the Electricity Consumption of Small Consumers in Case of an Hourly Pricing System. In: Advances in Automatic Control, Modelling & Simulation: Proceedings of the 15th WSEAS International Conference on Automatic Control, Modelling & Simulation. Romania, June 1 – 3, 2013, pp. 127 - 132.

Regression Analysis of Time Series for Forecasting the Electricity Consumption of Small Consumers in Case of an Hourly Pricing System

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Abstract: - Short-term electricity load forecasting is required for many functions, for example managing and controlling power systems, planning loads for power stations etc. In an open electricity market, load forecasting is necessary for electricity sellers, who have to buy necessary amounts of electricity from power exchange. Therefore, forecasting accuracy affects the seller's economic results. Also, accurate load forecasting could help retail electricity sellers to offer consumers real-time variable electricity tariff packages. A lot of different methods have been used for load forecasting and many novel methods have been proposed and designed. The aim of this article is to analyze 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. In addition, it gives an overview of the accuracy of regression analysis of time series method, and shows how to correct the day-ahead forecast error when forecasting two hours ahead. The results of this study demonstrate that regardless of a very large stochastic component, a relatively accurate load forecasting is possible when using the regression analysis of time series method. This article also shows how electricity sellers could use regression analysis of time series method to forecast load in order to offer consumers a real-time electricity pricing system. In addition, the regression analysis of time series method based forecasting model proposed in this article can also be used by electricity sellers to make optimal purchases from power exchange and increase their rate of profit.

Key-Words: - regression analysis, real-time pricing, time series forecasting, short-term load forecasting, load forecasting based on temperature.

1 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 electricity prices for consumers. Government-owned Eesti Energia AS, the biggest energy company in Estonia, currently possesses the largest market share which is approximately 70%. All the retail sellers are buying electricity either from the power exchange Nord Pool or directly from producers. Although there were some expectations that more different tariff systems would be introduced to 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:

- a. Fixed price tariff system,
- b. 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. When considering the design of Nord Pool power exchange and the purpose of retail electricity sellers to sell electricity that is calculated on the basis of 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. Currently, 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). The working principles of Elspot and Elbas are described in more detail in [1].

The authors have previously proposed an algorithm for real-time pricing system, which could be used with current market and power exchange rules. In the mentioned article, the authors also explained more specifically why a real-time pricing system is

necessary and showed how electricity retailers could offer consumers real-time prices based on the algorithm and current market/power exchange rules [1].

To initiate a real-time pricing system, it would also 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. For this study, we used already installed remotely readable meters.

Weather undoubtedly affects consumer load. There are a lot of meteorological factors that affect consumption like for example temperature, wind, etc [2]. However, since the effects of these factors on load are difficult to assess, only temperature dependence was chosen to be the basis of this research.

The aim of this article is to analyze the dependence of load on temperature, and to show that the regression analysis of time series method is accurate for short-term load forecasting and that it would allow the retail sellers to offer consumers a real-time electricity tariff system.

2 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 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:

- a. Short-term load forecasting, ranging from one hour to one week;
- b. Medium-term forecasting, ranging from one week to one year;
- c. Long-term load forecasting, ranging from one year to longer time periods.

Up until recently, consumption forecasting 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, forecasting should be easier and more accurate.

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

- a. Regular changes, like day-and-night, weekly and yearly periodicity, trend and nature of the load on national holidays;
- b. 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;
- c. Dependence on operating values, which is expressed as load voltage and frequency sensitivity;
- d. Randomness, which is particularly noticeable in loads of small distribution grids. The relation of this kind 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;
- e. 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 [3].

There are many different methods for load forecasting that are based on regression analysis, time series, neural networks, box-jenkins models, expert system approaches, artificial neural networks (ANN), etc [4]. The most commonly used forecasting techniques are neural network algorithms, time series approaches, regression techniques and expert system approaches [5]. A method is chosen primarily by taking into account the character of 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 [6].

Difficulty in load forecasting arises due to its nonlinear and irregular variation [7], which forecasting is complicated, if not impossible.

If weather condition is taken into account in forecasting load, then the load is given in the following form:

$$l(t) = l_a(t) + l_i(t) + l_d(t) + l_n(t) \quad (1)$$

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 [6].

Independent and stochastic components 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 other abnormal situations such as thunderstorms, etc [2] [6]. Nevertheless, it is important that a forecasting model is simple, accurate and convenient to use. In particular, it is necessary to distinguish 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 [6]. Therefore, in this study we analyzed whether and how much loads in Estonian households depend on the outside air temperature. In addition, we examined whether the proposed regression analysis of time series method is suitable and sufficiently accurate for electricity sellers to use for forecasting.

3 Overview of the proposed approach of regression analysis

For this study, the authors have chosen regression analysis for load forecasting because this is suitable for forecasting loads based on time series. 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:

$$l(t) = l_e(t, C, b) + \theta(t) \quad (2)$$

where $l(t)$ stands for actual load, $l_e(t, C)$ for mathematical load expectation, $\theta(t)$ for stochastic component, t for time, C for temperature, and 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 as described above. In this work, however, we are taking into account three main factors that affect load:

- Day (weekend, working day etc.),
- Time,
- Temperature.

Our study is based on measurements taken in Loo village near Tallinn 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 hours. After sorting out various erroneous measurements, 6497 hours of data, i.e. 74% of the data remained.

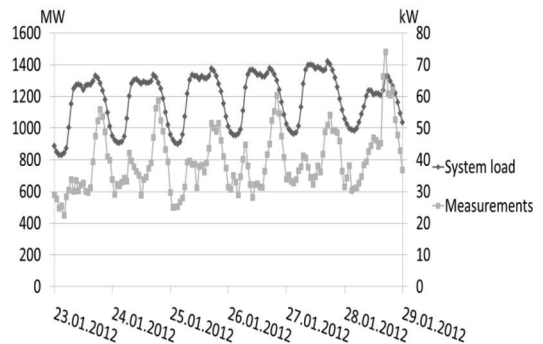


Fig. 1. Estonia's whole power system load and measurements carried out in Loo village during the period of January 23rd – 29th of 2012.

Fig. 1 shows a comparison of Estonia's 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 figure shows that, in general, the load curves are similar, however, in case of measurements carried out in Loo village, the consumers and all the unpredictable changes are strongly 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 [3]. Inertia and temperature sensitivity are different for every customer and depend on the heating system and on the construction of the building. In this work, however, separate inertia 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 figure shows a strong correlation between temperature and consumption. 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.

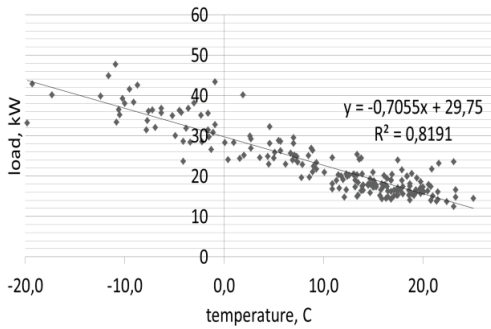


Fig. 2. Correlation between load and temperature during working days at 1 p.m.

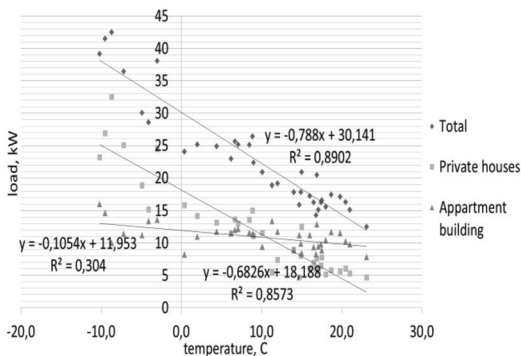


Fig. 3. Correlation between load and temperature on Mondays at 1 p.m.

For Fig. 3, different working days were separated and a correlation between load and temperature on Mondays at 1 p.m. was analyzed. The coefficient of determination R^2 shows how a large part of the

measurements is explainable with the proposed method. This figure also shows that the actual loads on different days varied and the consumers had different habits. Thus, differentiating weekdays results in a much stronger dependence between temperature and load.

The Fig. 2 and 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 [8] [9].

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 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:

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

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 $^{\circ}C$).

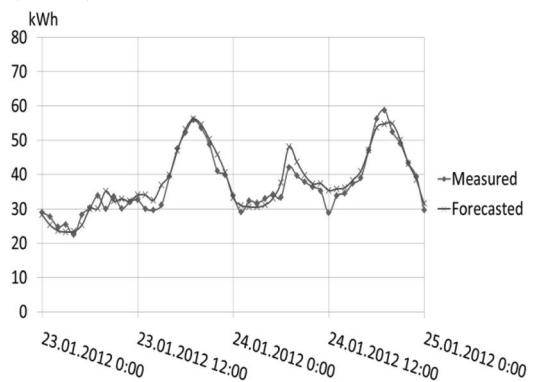


Fig. 4. Measured and one-day-ahead forecasted consumption during the period of January 23rd – 24th of 2012.

Fig. 4 shows the measured and one-day-ahead forecasted loads. For load forecasting, we used actual temperatures measured in Harku's meteorological station. The figure shows that on a large scale, the predicted and the actual load curves coincide. The load, however, is affected by irregular changes, which cannot be forecasted in advance. In order to compensate the one-day-ahead forecasting error, we used the function:

$$l_{Elbas}(t+2) = l_{Elspot}(t+2) + l_{Elspot}(t+2) \cdot \frac{\sum_{t=-4}^{-1} [l_a(t) - l_{Elspot}(t)] \cdot \alpha_t}{4 \cdot l_{Elspot}(t)} \quad (4)$$

where $l_{Elbas}(t+2)$ 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.

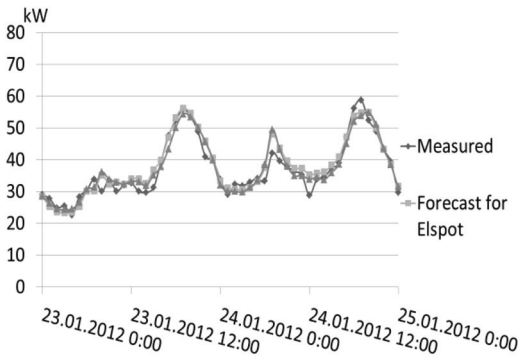


Fig. 5. Measured, one-day-ahead forecasted and two-hours-ahead forecasted consumption during the period of January 23rd – 24th of 2012.

In order to give a higher priority to the newest data against the oldest values, we use 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. 5 shows the loads calculated with formula 4 two hours ahead, as well as the actual load and the forecast one day ahead. It is clear that the formula 4 is reducing the difference between the day-ahead forecast and the actual load.

At the same time it should be noted that in certain situations, using the formula 4 can cause a larger difference between the actual and the forecasted load. However, all in all 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, 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. When using the formula 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 mean absolute percentage error (MAPE), which is used for evaluating model performance, for day-ahead forecasting was 14.17% and for two-hours-ahead forecasting was 10.70%. MAPE is calculated with the following formula:

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

where $l(t)$ stands for actual load, $l_e(t)$ for mathematical load expectation, and N for population of the evaluation set [10] [11].

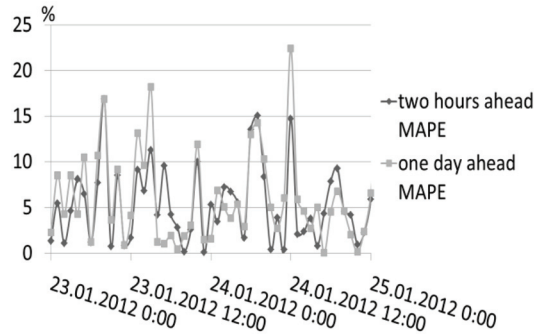


Fig. 6. MAPE for one-day-ahead forecast and two-hours-ahead forecast during the period of January 23rd – 24th of 2012.

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.

4 Conclusion

In this article, we used regression analysis of time series to analyze a small group of consumers in order to create a model for forecasting load one day ahead and two hours ahead. Usually, 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 analyzed individual consumption dependency on temperature of eleven private houses and one apartment building with 60 apartments in an Estonian village during 2012. Despite the fact that

some articles point out that methods based on weather conditions are not suitable for short-time horizon load forecasting [12], we still used temperature in the present work for load forecasting. Our work showed 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.

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. Although whole power system load is affected by a large number of different stochastic changes, the system load is not strongly affected by load changes of individual consumers and that makes the forecasting more accurate compared to smaller systems.

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 slightly 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 group of customers was analyzed 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.

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Paper IV

Kivipõld, T., Niitsoo, J. Overview of information and communication issues for smart grid solutions. 10th International Symposium “Topical Problems in the Field of Electrical and Power Engineering”, Doctoral School of Energy and Geotechnology II, Pärnu, Estonia, January 10-15, 2011, pp. 108-112.

Overview of information and communication issues for smart grid solutions

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Abstract

Shortage of conventional energy supplies force us discover new energy sources. Despite the global economy crisis started in 2008 the energy consumption is still growing. Construction of new energy plants is very expensive and therefore may be reasonable to optimize the consumption. Smart grid's one goal is to that with wise control of client's appliances. That should be done beneficially as for utility and customer. Smart client is essential in this process. This paper describes benefits of greater amount of information and communication solutions to provide this all.

Keywords

Smart grid, smart consumer, information of smart grid

Introduction

European Union has decided to deal with smart grid solutions quite intensively. There are many definitions for smart grid, but most of them contain idea of using new and innovative solutions to enhance the energy grid and it's parts.

Essential in this development is a customer who should be aware of the need for innovation and understand those new solutions. On another hand utility can gain from getting information about client's load profile and smarter clients in their grid.

Therefore it is crucial to work out solutions to communicate with customers and manage information reasonably. It all must be done economically beneficially and at same time guarantee client's privacy.

Also is important to figure out which kind of information different parties need. It is necessary to optimize information capacity and frequency of delivery and choose right communication solutions.

1 Information for smart consumer

Some smart meters installed over the world nowadays already allow bidirectional communication for controlling household devices, monitor electricity consumption and investigation of power quality. In Estonia there are only few

remotely readable meters which yet do not have any extra features but electricity consumption metering.

It is possible to build smart system with possibility to switch on/off consumer's equipment and compensate it to client in some way. It may be helpful for reducing demand peaks, but his solution might not be economical if price signal is delivered to consumer's apparatus and they react accordingly to that. In that instance a demand curve will be enhanced in real-time by market situation. On 1st of April 2010 Estonia opened its electricity market by 35 % and it will completely open in 2013 which creates good basis for implementation of market price based controlling systems.

Customers should have as much information as possible about situation of grid and his own apparatus. Data should be easily accessible and analyzable for all parties. On another hand amount of information should not exceed optimum. In other words information costs should not raise energy price. It puts boundaries to information's capacity and accuracy.

Gathered information from different clients has great potential for utility and third parties to help reduce customer's energy use, avoid costly outages and restorations. Also optimize complexity of modern household full of complicated and interactive appliances.

2 Benefit of information

All parties gain by adding intelligence to appliances (heating-, cooling-, lighting systems etc.) in buildings and households [1]. It also simplifies integration of distributed generators and diminishes emission of carbon dioxide.

Customers direct gains and prospects could be following [1, 2]:

- monitoring of energy consumption and of costs;
- compensation for optimizing demand (if utility offers any); quality;
- simpler overview of energy efficiency;
- simpler overview of energy profile;
- easier management, distribution and analysis

- benchmarking opportunity;
- finding energy wasting devices;
- controlling building's energy consumption;
- foresee maintenance of appliances;
- reduce environment pollution by saving energy;
- improved transparency of electricity bills.

Implementation of real-time measurement systems and delivering the price signal to customer would reduce Estonian peak demand approximately 5-8 % [3]. Peak demand decrease would smooth a load curve. It can be characterized by load factor. Load factor is calculated as following:

$$k_k = \frac{P_{avg}}{P_{max}} = \frac{W}{T \cdot P_{max}} = \frac{T_{max}}{T} \quad (1)$$

where k_k is the load factor, P_{avg} – the average load, P_{max} – maximal load, W – consumption during the period, T – time period, P_{max} – maximal load, T_{max} – maximal load duration.

Therefore it is important to investigate how real-time measurement systems will affect market demand.

Traditionally low voltage network management has been in complete off-line mode. On-line information has been available only from primary substations. The integration of Automatic Meter Reading (AMR) makes it possible to cost-effectively monitor a low voltage network and analyze fault situations since AMR communication infrastructure can be used. Network monitoring in Supervisory Control and Data Acquisition/ Distribution Management System (SCADA/ DMS) requires that events from meters are received in a near to real-time manner. [4]

Management of a low voltage network may create following functions [2]:

- automatic fault or interruption identification;
- fault location identification;
- accurate fault data transmission;
- real-time power quality measuring;
- meter control;
- integration of distribution generators.

3 Power quality monitoring

Power quality at client's connection point has been measured only occasionally. Power quality measuring constantly all over the grid would help to plan and prioritize investments.

Comprehensive quality measurements would give information about many processes in a grid. The development of systematic procedures for power quality data management supports in general [4]:

- customer services (e.g. quality reports, clarifying customer requests, planning of compensation of reactive power, instructions for the use of various equipment);

- distribution network design and operation (e.g. investment plans and management of voltage drops and fluctuations, harmonics and other disturbances);
- outage statistics (e.g. needs of the Energy Market Authority).

In Estonia sum of claim damages has been decreasing, but numbers are still quite large. Hence it is still huge problem to deal with. Exact figures are shown at Table 1.

Table 1. Statistics of customer's claim damages [5]

	Claim damages	Compensated damage, MEEK
2008/2009	1229	3,4
2009/2010	817	1,5
2010/2011*	782	0,6

* First 10 months of financial year

Usually 80 % of all claim damages are matter of voltage quality and 30 % of them are compensated [5]. Other claim damages are not clarified because of different reasons.

It probably would be wise to begin with evaluating new smart meters project's profitability and sustainability by using net present value method:

$$NPV = \sum_{i=0}^n \frac{B_t - C_t}{(1+i)^t} = \sum_{i=0}^n (B_t - C_t)(P/F, i, t) \quad (2)$$

where NPV – is net present value, C_t – is a total costs, B_t – is a total revenue, n – is the evaluation period (meters life time), i – is interest rate or discount rate.

Comprehensive monitoring of customers' power quality may create new billing opportunities. For instance it would be easier to charge customers dependently on power quality. Also is prospect to tax all customers for using reactive energy.

4 Interactive communication

For developing distribution management and the functionality of the electricity market, one essential objective is to make the customer active for improving and provide:

- interconnection of distributed generation;
- efficient use of energy;
- market-based demand response;
- quality of supply enhancement;
- management of active distribution networks.

The interactive customer gateway enables [4]:

- more efficient and flexible network interface, e.g. for Distributed Generation (DG) and plug-in hybrid cars;
- on-line market (price) oriented load and DG control management;

- frequency based load control during local or system level load and generation unbalance situations;
- services for energy savings and efficient use of energy;
- on-line management and control of customer voltages, also including elimination of short interruptions (i.e. reclosing's and voltage dips);
- more reliable constructions in distribution networks and advanced management of active distribution networks using data on interactive customer gateway.

5 How to manage information

Individual consumer data usually belongs to the consumer or to a data carrier company. In addition, it is possible for network companies, subcontractors or third parties to access collected data. There could be a number of benefits for the latter. Therefore, third parties should be considered when making laws. Other ways, it may happen that the new laws exclude their participation. [6]

If the information additionally includes geographic, demographic and meteorological data, then the data could be even more useful and more desirable for analysis. The third parties would be able to examine how consumers use electricity (even by separate devices), how consumption is related to price, family income, family size, etc. [6]

Intelligent metering system provides us with real-time information about various groups of consumers, it enables to detect whether some device is on or off, the changes in temperature, air, etc. This kind of monitoring system allows us to identify devices that are wasting energy, such as computers and TV-s at stand-by mode [2]. Thereby each consumer profile is developed, which facilitates the overall analysis. Secondly, it will simplify forecasting load in electricity market.

Under "real-time" concept various time intervals are meant, for example 5, 10, 15, 30, etc. minutes. The question is to whether a 5 minute information interval is necessary or is the 15 minute information interval also sufficient to make change in demand curve.

The usage of smart meter enables to research voltage peaks and dips, transients or current waveforms and harmonic contents in order to identify sources that cause problems in networks. Some common faults have their own pattern of failure that can be used for identification. For example in case of a voltage dip should be controlled [2]:

- voltage dip magnitude and duration;
- current waveform;
- waveform of second transformer (in case there is more than one supply transformer);
- other equipment and their transformations;
- power flows.

6 Communication solutions

Intelligent communication solutions are the inseparable part of smart grid. High performance smart grid applications require two-way communications, and should take place almost in real-time between centralized control system and millions of smart grid devices. Communication network, that is designed for the smart grid and must have highest reliability, is certainly a critical part. It has to be optimized and almost certainly constitutes a large part of smart grid construction costs. [7] There should be a two-way communication [8] meaning that smart metering data are transmitted to grid operator and grid operator sends price signals to smart metering system.

The key issue in finding communication solutions lies in the structure of smart grid. Based on smart grid structure, the communication solutions, standards and security requirements will be selected and worked out.

The security of communication solutions is one of the most important topics that should be researched in depth. Smart meters could be one of the weakest links in smart grid security. The users have physical access to the meter and its wireless connection interface could potentially attract malicious users trying to break through and inflict damage.

When building a smart grid, various communication solutions are to be considered. In case of existing communication solutions, it is important to use already installed solutions if possible. The most common possible communication solutions are optical, wireless, PLC, WiMax, GPRS, Ethernet, radio, etc. When considering various communication solutions, bandwidth, security and response time need to be taken into account. Although many different solutions are in use for reading metering data, it would be important to investigate which communication channels are feasible.

In addition to the conditions above, the data rate, which passes through the communication system, must be taken into account. It is likely that typical smart devices measure line voltages and currents. Assuming that the parameters are measured 16 times per 50 Hz cycle, 960 measures will be produced per second for each measured parameter, approximately 1 Ksample/s/parameter. If the analog to digital conversion uses a 16 bit word, the acquisition results in a 2 Kb/s/ parameter throughput. Such a sampling rate results in a built-in delay of 1 ms for any process in need of sampled data. For example 3 voltages and 3 currents are to be sampled, a basic 12 Kb/s is required to broadcast the raw data samples. It is expected that besides raw data, computed quantities (i.e. phase amplitude, phase angle, sequence components, etc.) will increase the bandwidth requirement to around 200...500 Kb/s or to 2...5 Mbits/s. Of course, these data rates must be supported by a communication protocol which will make use of additional information, such as node

addresses, data error detection/ correction, packet and message routing, etc., resulting in an increased bit rate. The 2...5 Mbits/s data rate should be considered indicative of an application with a relatively low to medium data rate production and may be used as a guideline. [9] Necessary data rates must be researched more adequately to make absolute conclusions.

Currently Eesti Energia Jaotusvõrk OÜ has installed different remotely readable meters. Different meters use different kind of communication solutions. Some of them have additional features e. g. AIM1 can record voltage interruptions (time, durability), current and voltage limit disruptions. All the information about installed remotely readable meters is in Table 2.

Table 2. Eesti Energia Jaotusvõrk OÜ remotely readable meters [5]

Meter name	Installed meters	Where	How system works
Treng	18 000	Installed in (approx. 240 pc) apartment buildings in Tallinn	Meter pulse outputs are collected through intermediate panels to stairwell terminals. Connection between meters and terminals is mediated through cables. Terminals are connected to a substation concentrator by PLC. Concentrators send information to the control station by GSM. In some cases, information is sent directly from stairwell terminals to control station using GSM. The reading takes place once a month.
Ektaco TAXERNET	17 000	Installed in apartment buildings in Tallinn	Meters pulse outputs are connected to a taxer that is connected by a communications cable to concentrator. 20 % of concentrators use GSM communication to send information to control station and 80 % use cable television network. Data are collected once a month, whenever Eesti Energia Jaotusvõrk OÜ wants.
Enermet	514	Installed all over Estonia	Information is sent to concentrator by 0.4 kV power line carrier and concentrator sends information to control station by GSM. Data are collected once a month.
AIM1 (Lamndis and Gyri's modern system, nowadays new measuring points are added)	11 000	Installed in commercial buildings	Most of them are P2P meters, which means that meters have integrated modems and data are sent by GPRS. Data are sent directly from meters to control station and once a day hourly data is read. In this case, depending on the type of meter, it is possible to record voltage interruptions (time, durability), current and voltage limit disruptions.
AIM 2 (Lamndis and Gyri's modern system)	9 000	Installed in apartment buildings and private houses	Communication between meters and concentrators uses power line carriers. Concentrators use GSM to send information to control station and are located in substations.
Kamstrup	68	Installed in one apartment building	Inside the building radio-mesh is used to collect data into master meter, which sends information to control station by GSM. Readings are collected once a month.

In addition, Televõrk AS internet solution called KÕU could be considered for data transferring from smart meters or other grid measuring devices. KÕU covers almost all of Estonia and is a Code-Division Multiple Access (CDMA) network. More than 95 base stations are installed all over Estonia and it uses low radio frequency 450 MHz. KÕU bit rate is up to 2 Mbit/s, which is enough to send electricity meter readings. In addition, it is possible to use wireless links in Estonia:

- GPRS – spreads all over Estonia, speed is up to 50 Kbit/s;

- 3G – a small coverage area, speed is up to 2 Mbit/s;
- WiMax – spreads all over Estonia, but needs direct line of sight with a communication mast, speed is up to 2 Mbit/s.

Communication infrastructure is a very complex task. Smart grid is accompanied by combined implementation of various renewable sources, consumer behavior adds indeterminacy, and new technologies (e.g. electric cars) take the complexity of the system to a whole new level. [10]

When choosing communication solutions, different parts of the electrical system should be observed separately and it should be considered how important the information is and how fast the information should be transmitted from one point to another.

Teleprotection requires extremely high network reliability. Errors in teleprotection may cause electricity system failures and risk to human lives. Therefore, such systems should use reliable communication links, for example power line carrier (PLC) or optical cables. [11]

In distribution system there is a very wide range of different devices, which means that there are thousands of different measurement and control points. One way to collect all the data from thousands of points is to use wireless communication solutions.

Development of communication system architecture is one of the most important parts of smart grid. Development mistakes in communication architecture may cause a lot of problems in a later stage. For example it could prevent smart grid development into a fully integrated system. [10] Fixing mistakes can later cost several hundreds or even millions. That is why it is vital to think through, how the communication system architecture should turn out to be.

Conclusion

Smart grid involves vast amount of information that needs to be transmitted, monitored, recorded, analyzed, etc. This means a great amount of different data and that the system must operate continuously. Therefore reliable communication networks need to be chosen. In addition, consumers should be able to understand all the information which they are given and at the same time they should be able to orient and make the right decisions. Thus, building a smart grid is merely not enough, it is also important to have a smart consumer.

Increased amount of information may give a lot of advantages, but it must be properly managed, in order to avoid risks to consumer privacy. Also it is necessary that reliability of system increases while costs do not rise.

There is variety of remotely readable meters installed in Estonia, but most of them cannot measure anything but electricity consumption. It is therefore essential to estimate whether their further installation is cost-effective and sustainable.

It is important to provide as much information as possible to consumer and at the same time distinguish significant and insignificant data. Communication solutions have to be reliable and already installed solutions should be used if possible.

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Paper V

Kivipõld, T., Valtin, J. 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. *International Journal of Energy and Environment*, Issue 5, Vol. 7, 2013, pp. 221-228.

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

T. Kivipõld and J. Valtin

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

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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

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-jenkins 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]:

$$l(t) = l_a(t) + l_i(t) + l_d(t) + l_n(t) \quad (1)$$

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:

$$l(t) = l_e(t, C, b) + \theta(t) \quad (2)$$

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.

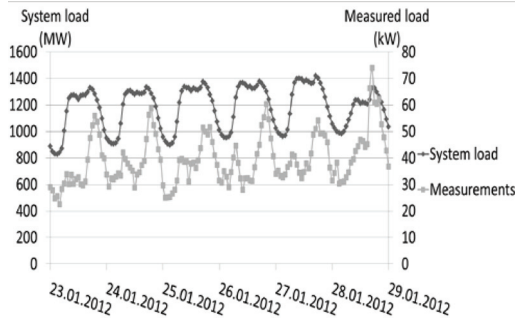


Fig. 1 Estonian whole power system load and measurements carried out in Loo village during the period January 23rd – 29th of 2012.

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.

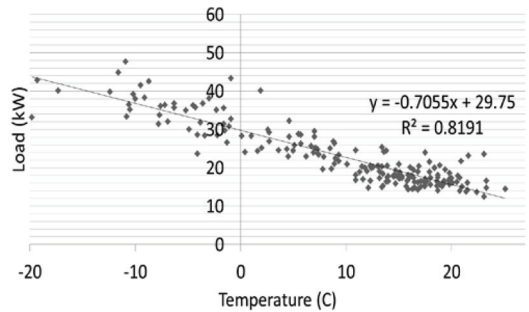


Fig. 2 correlation between load and temperature on working days at 1 p.m.

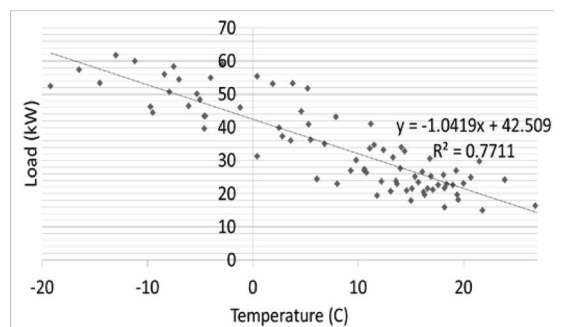


Fig. 3 correlation between load and temperature on days off at 1 p.m.

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.

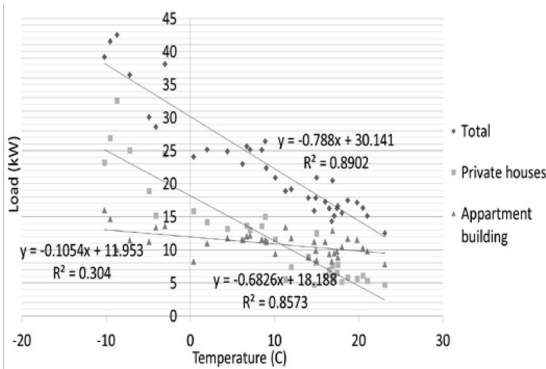


Fig. 4 correlation between load and temperature on Mondays at 1 p.m.

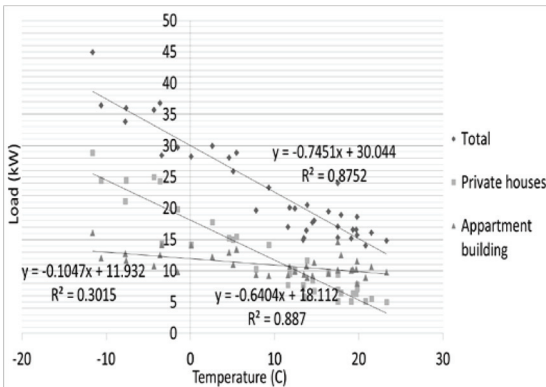


Fig. 5 correlation between load and temperature on Tuesdays at 1 p.m.

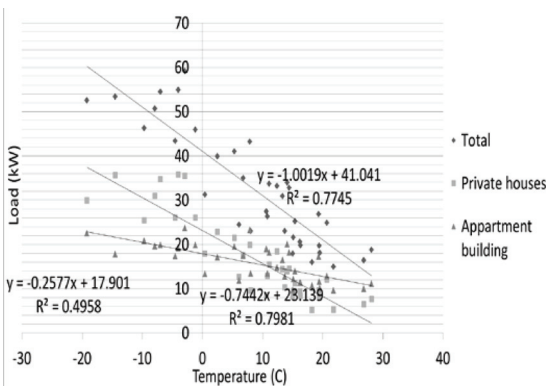


Fig. 6 correlation between load and temperature on Saturdays at 1 p.m.

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:

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

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 °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.

Consumption

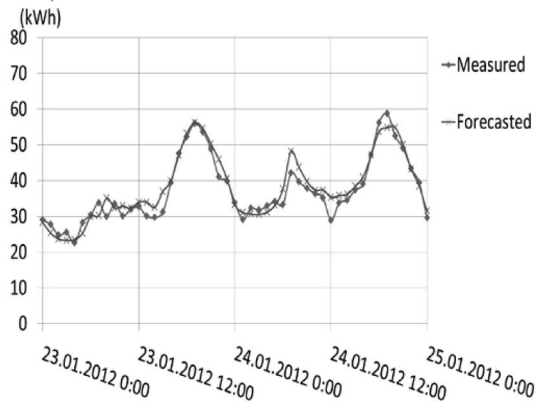


Fig. 7 measured and one-day-ahead forecasted consumption during the period of January 23rd – 24th of 2012.

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:

$$l_{Elbast}(t+2) = l_{Elspot}(t+2) + l_{Elspot}(t+2) \cdot \frac{\sum_{i=t-1}^{-4} [l_a(t) - l_{Elspot}(t) \cdot \alpha_i]}{4 \cdot l_{Elspot}(t)} \tag{4}$$

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_i 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.

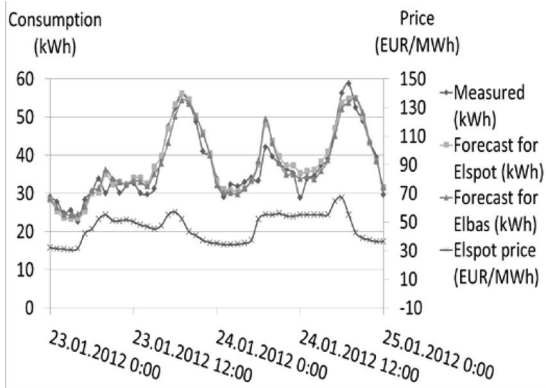


Fig. 8 Measured and forecasted consumption and Nord Pool prices during the period of January 23rd – 24th of 2012.

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]:

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

where $I(t)$ stands for actual load, $I_e(t)$ 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.

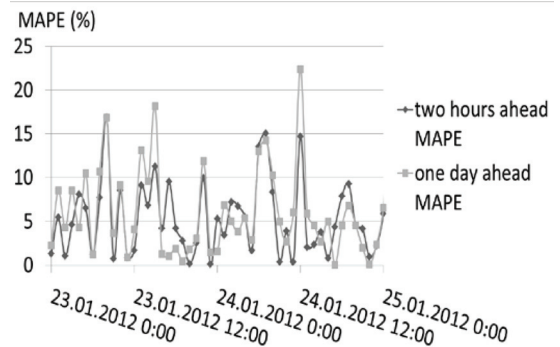


Fig. 9 MAPE for one-day-ahead forecast and two-hours-ahead forecast during the period of January 23rd – 24th of 2012.

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:

$$S_{E,t+1} = S_{t,elspot} + S_{t,elbas} + S_{Commission} \tag{6}$$

where $S_{t,elspot}$ stands for Elspot's electricity price, $S_{t,elbas}$ for Elbas' electricity price, $S_{Commission}$ 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:

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

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

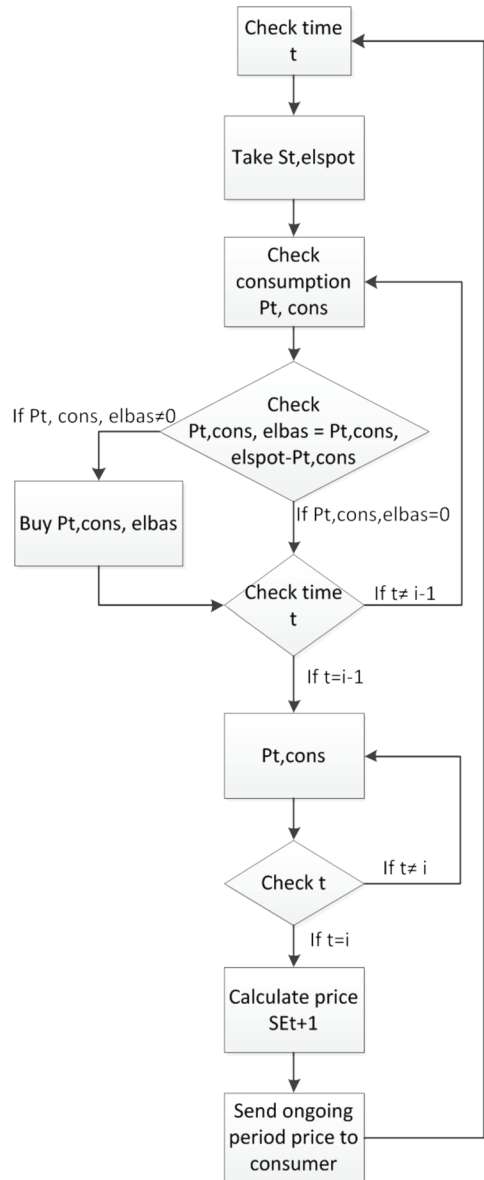


Fig. 10 proposed algorithm for calculating the electricity price and sending it to the customer.

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:

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

where $L_{Elbas,t+2}$ stands for required power from Elbas,

$I_{Elbas}(t+2)$ for predicted load for the next hour.

When $I_{Elbas}(t+2) = I_{Elspot,t+2}$, 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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Paper VI

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Power Quality Issues in Dispersed Generation and Smart Grids

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Abstract—The world today is moving toward smart distribution grids and dispersed generation. Those tendencies are caused by different reasons. These include the decrease of fossil fuel consumption, EU directives of CO₂ emissions and climate objectives etc. Innovation and change in technology is a highly welcomed trend but one must not forget that there are drawbacks as well as benefits. One of the most important issues in future grids are the power quality and supply reliability issues. This paper describes how the change to dispersed generation and smart grids should look like and what are the main problems, that need quick and active solutions, so that future grids would be fully functional and reliable.

Index Terms—Power distribution faults, smart grids, power system dynamics, harmonic distortion.

I. INTRODUCTION

If centralized generation is characterizing factor for nowadays energy systems, then smart grids of the future mean also the spreading of dispersed generation. The cause of these changes is the strict environmental norms and liberalization of electricity markets [1].

Dispersed generation has been recommended as one of the environmentally friendly solutions for improving the energy system, decreasing the losses and increasing effectiveness [2]. In addition increasing the ratio of small producers in electricity generation has been proposed.

Connecting new producers and generators to the distribution network can drastically change the working parameters of the grid. This situation is extremely important when the new connected power plant is equal to or even greater than the load in this particular area. In such case the new power plant affects the voltage adjustment and power flux. It is important to evaluate the existing grid, capacity and loads in this certain area of the distribution network [2].

Dispersed units affect the current quality and through the grid also the voltage quality as experienced by other

customers [2]. Power quality concerns the electrical interaction between the network and its customers. It consists of two parts: the voltage quality concerns the way in which the supply voltage impacts equipment; the current quality on the other hand concerns the way in which the equipment current impacts the system [3].

For these reasons it is important changing of the loads have to be observed in smart grids as well as the growth of dispersed generation. In addition loads are getting more and more nonlinear which means that the cooperation of untraditional generation and loads affect the grid in unpredictable ways.

One of the key aspects of electricity production and distribution is the power quality and supply reliability for the customers. Traditionally the problems have been solved but as the world is moving towards smart grids and dispersed generation, those problems need more active and precise control.

As it can be expected, a great number of small generation units will be connected to distribution grids in quite near future. Most probably it would require certain online diagnostic systems to secure the full functionality and reliability of those units.

As due to the rise of harmonics in the grid, the machines would become more vulnerable, their faults become even more difficult to detect, so one could expect a growing number of unexpected downtimes due to different faults of the generators. This is the issue why real time condition monitoring is of utmost importance in the dispersed generation situation.

II. DISPERSED GENERATION

Dispersed generation is the production of electricity at or near the point of use. Most or part of consumed energy is produced at point of use and rest of the electricity goes into the distribution grid [3].

In most cases it is assumed that the electrical current and voltage have a sinusoidal wave shape. But if hundreds or thousands of small power production plants are connected to

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a grid, it could mean that the sinusoidal current and voltage waveform are distorted and the waveform is no longer sinusoidal. Also, all small generators themselves produce harmonics. So the large-scale use of renewable energy sources for the production of electricity will bring major challenges for the electricity network.

Generators are typical electrical devices that are usually setup together with frequency converters to drive them and different inverters to synchronize their work with the grid. Not only generators themselves but also frequency converters and other electronic devices produce a vast number of harmonics that can be a problem to electrical machines they are set up with and also the grid they are working in. Due to financial benefits usually no additional filters are used to lessen the amount of induced harmonics. A typical harmonic distortion of a frequency converter is shown on Fig. 1.

As dispersed generation means also a growing number of small power plants such as small hydro and wind applications, this harmonic problem can become a serious issue for the power quality and supply reliability in smart grid or dispersed generation situation.

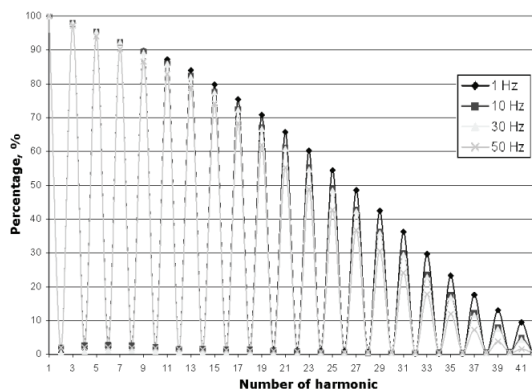


Fig. 1. Typical harmonic distortion of frequency converter.

For showing the probability of large extent of distributed generation in near future the potential is pointed out. The Estonian potential for dispersed generation, which currently is greater than the annual electricity consumption, is chosen as the example [3]. The potential of different energy sources in Estonia are shown in Table I.

TABLE I. ESTONIAN POTENTIAL OF DISPERSED GENERATION [3].

Name	Energy MWh/year	%
Wind energy	6 224 400,00	53
Litter oddments (biomass)	1 280 400,00	11
Wood (biomass)	1 279 800,00	11
Boiler plant reconstruction to CHP	1 179 000,00	10
Energy brush (biomass)	1 079 133,30	9
Solar Energy	224 000,00	2
Dung (biogas)	185 435,20	2
Hydropower	102 514,00	1
Reed (biomass)	50 000,00	0

Name	Energy MWh/year	%
Landfill gas (biogas)	25 974,40	0
Wastewater sludge (biogas)	21 201,60	0
Total:	11 651 858,50	100

III. POWER QUALITY

Connection of dispersed resources and changing dispersed generation to the distribution grid can affect the power quality in a great amount [2]. Smart distribution grid must secure the end users with power that has the demanded quality [4]–[6]. This is why the modern control systems, that are monitoring the important components of the distribution grid, must react precisely to the changes in power quality.

Power quality can be controlled and improved in whatever point of the electric system beginning from the means in the system or the grid and ending with single devices at the consumer level.

Connection of the dispersed generation of renewable energy to distribution grid can have both positive and negative effects to the power quality. It depends on possibilities of information and communication systems to control and maintain voltage in the feeders, turn the loads in or out and replace lost power with the reserves.

For example small amounts of wind power have negligible effects on electricity networks, but when electricity generation from wind power exceeds a certain threshold level, investments in the power system will be required. This threshold level is known as the hosting capacity [4].

The principle of hosting capacity is explained at Fig. 2. Hosting capacity does not say anything about how much generation from renewable energy sources that is connected to the grid, only how much can be connected without having to invest in measures to strengthen the grid.

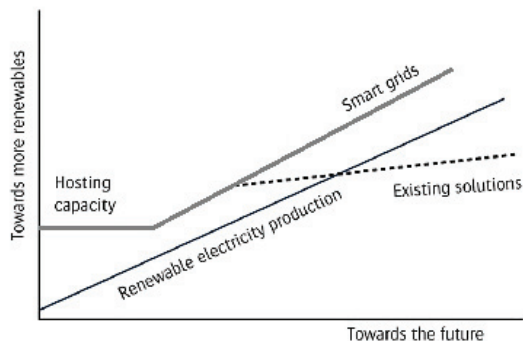


Fig. 2. The principle underlying hosting capacity [5].

IV. HARMONIC DISTORTION DUE TO DIFFERENT LOADS

Electrical devices, which are coming onto market, are becoming more and more complex. They may help to reduce energy consumption, but their performance regarding power quality is still rather improper.

The problem is that their current curve is not a perfect sinusoid. The widespread use of nonlinear loads may

implicate significant reactive power and problems with higher harmonics in a grid [6].

Harmonic currents produced by nonlinear loads are injected back into the supply systems. These currents can interact adversely with a wide range of power systems equipment causing additional losses, overheating and overloading. These harmonic currents can also cause interference with telecommunication lines and errors in power metering [7]–[9]. That problem may come more important when smart grid solutions where communication is very important are adapted.

Typical current curves of nonlinear loads are shown at Fig. 2. While the applied voltage is almost perfectly sinusoidal, the resulting current is heavily distorted.

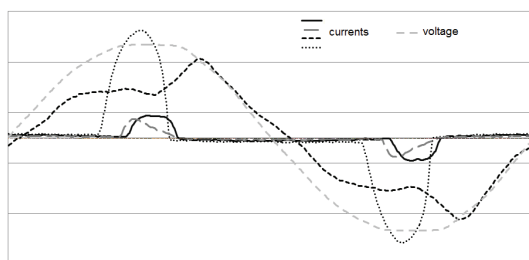


Fig. 3. Currents of typical nonlinear loads versus voltage.

Harmonics generated by consumer's appliances must not cause voltage rise in the connection point [6]. Fixing limits may become important before using numerous harmonics emitting devices together. In some papers [8] measurements with nonlinear loads are done when 5% current's total harmonic distortion value at connection point is followed. For example most of the common compact fluorescence lamps have the total harmonic distortion over 100% [9].

Harmonic currents injected from individual end users on the system should be limited. These currents propagate toward the supply source through the system impedance, creating voltage distortion. Thus by limiting the amount of injected harmonic currents, the voltage distortion can be limited as well. This is the basic method of controlling the overall distortion levels proposed by IEEE standard 519-1992. Example for illustrating nonlinear loads influence on distribution grid a study with compact fluorescence lamps (CFLs) is made [8], [9].

V. POSSIBLE SOLUTIONS FOR POWER QUALITY FALL IN SMART GRID

Equipment responds very differently to harmonic distortions, depending on their method of operation. For example incandescent lights and different household heaters are not affected by them. On the other hand, induction motor windings are overheated by harmonics, causing accelerated degradation of insulation and so the lifetime of the machine can shorten in an abrupt way. The problem is that harmonic voltages can give correspondingly higher currents than do 50 Hz voltages and one can easily underestimate the degree of additional heating in the motor [10].

It is a widely known fact that faults such as the broken

rotor bars induce sideband harmonic components to the stator current spectrum of the induction machine. Those harmonics can be used for detecting the faults. As most of electrical machines today are used in hand with frequency converters, then those converters add additional variables to the problem. Frequency converter causes supply frequency to vary slightly in time and, as a result, some additional harmonics in the current spectrum are induced and sidebands are reduced [11] or even hindered. This phenomenon also raises the amount of noise in the test signals, which makes the faults more difficult to detect.

In that sense it could prove to be useful to use a certain on-line diagnostic system in the grids with dispersed generation and the wind generators that are integrated to this system. This could be a helpful tool to detect the faults at an early stage where the repairing of the machines is still possible and reasonable. Also it would help to differentiate the deviations and harmonic distortions in the grid from the faulty cases of the machines.

VI. CONCLUSIONS

Irrespective of how the term smart grid is defined, one can safely state that electricity networks will face new challenges in the future, and that current and future challenges can be solved by a set of technologies that either exist today, or are being actively developed.

If more and more dispersed generation is going to be installed all over the power networks like it seems to go then it is most important to find measures for guarantying quality and security of supply.

From the example of Estonia we can see that the potential of dispersed generation is extensive. The impacts of using distributed generation may be massive even if bulk of that potential will not be installed.

In the situation where generation as well as consumption produces decrease of power quality in the grid, it is essential to analyze both generation and consumption in a very thorough way. If it proves to be necessary it might make sense to limit the usage of new plants and appliances or use some other methods to decrease their negative effect to power quality.

Usage of nonlinear loads like compact fluorescent lamps has risen rapidly in the last decade, but their harmonic emission, reactive power consumption and other drawbacks have been ignored.

Beside the problem that harmonics are extremely dangerous to electrical motors, distorted supply makes the diagnostics of them more difficult. A growing number of machines are driven through frequency converters. This means that also diagnostic for appropriate setups with frequency converters should be investigated. Frequency converters add additional noise and harmonics to the traditional current spectrum of the machines and thus such drives need a slightly different approach in diagnostics than traditional grid supplied machines. Nevertheless, appropriate on-line diagnostics of dispersed generation units must be applied to guarantee sufficient power quality, supply reliability and overall safety of customers and different

facilities connected to the grid.

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