RIGA TECHNICAL UNIVERSITY
Faculty of Power and Electrical Engineering
Institute of Energy Systems and Environment

Ilze LAICĀNE

THE TRILEMMA OF ELECTRICITY USERS

Summary of doctoral thesis

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**DISSERTATION PROPOSED FOR DR.SC.ING. DEGREE
IN ENVIRONMENTAL ENGINEERING AT
RIGA TECHNICAL UNIVERSITY**

This study is proposed for attaining the degree of Dr.sc.ing. in Environmental Engineering and will be defended on July 2, 2015 at 2:00 p.m. at the faculty of Power and Electrical Engineering, Āzenes iela 12/1, Room 115.

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CONFIRMATION STATEMENT

I, the undersigned, hereby confirm that I have developed this dissertation, which is submitted for consideration at Riga Technical University, for attaining the degree of Dr.sc.ing. in Environmental Engineering. This study has not been submitted to any other university or institution for the purpose of attaining scientific degrees.

Ilze Laicāne ……………………………… (signature)

Date: 02.07.2015.

The dissertation is written in Latvian on 183 pages, contains an introduction, 4 chapters, conclusions a bibliography, 49 figures, 18 tables, 72 mathematical formulas and equations and appended 7 annexes. The bibliography contains 235 references.

TABLE OF CONTENTS

TOPICALITY OF THE WORK

Along with rapid economic development, population growth, livelihood increase and striving for better life quality and higher comfort level, electricity consumption in the household sector has significantly increased. That creates global environmental problems, such as changes in the Earth atmosphere, increase of CO2 emissions, impoverishment of energy resources, increase of costs for resources extraction, etc. At the global level, electricity consumption in the households sector constitutes approximately 28-30 % of the total end-use electricity consumption in the other sectors. In Latvia, households are the second main consumers of electricity after the commercial and public sectors. In 2013, households consumed 27,11 % of the total yearly end-use electricity consumption, creating around 7% of total yearly GHG emissions in Latvia [1, 2].

Sustainable energy (including electricity) consumption and energy efficiency increase are one of the main principles of energy and climate policy in Europe and Latvia. Strategies aimed at environmentally friendly development, creation of action plans and application of systems thinking are the most rational and appropriate approaches to solving environmental problems in specific conditions. One of the most significant instruments to ensure sustainable energy consumption is implementation of energy management system for consumption reduction (Demand Side Management – DSM) that can be applied at the state and municipality level, in enterprises and institutions of different sizes as well as in the households [3]. In order to comply with "20-20-20" targets by the year of 2020, in the "Climate and Energy Legislative Package" in 2008, European Parliament and Council integrated conditions, which foresee renewable energy, advanced materials and improved DSM introduction into all end-use sectors. DSM allows to perform monitoring and achieve sustainable practice of rational energy use [4]. DSM implementation in the households sector can provide significant potential for energy efficiency improvement. The aim of DSM is to decrease energy consumption at all system's stages through overall improvement of energy use and energy efficiency along with maintaining of improving user's comfort level. DSM integration at a wider scale can lead to the development of low-carbon society.

European Union (EU) member states with the corresponding planning documents and legal acts have approved their willingness and actions towards energy efficiency enhancement [3]. Directive 2006/32/EC of the European Parliament and of the Council states that by the year of 2016 the member countries are obliged to achieve energy consumption reduction by 9% as a result of energy efficiency measures [5]. Meanwhile, in the year of 2012, the new target was set in the Directive 2012/27/EC, which obliges for end-use consumption reduction by 20% by the year of 2020 and establishment of the basis for further energy efficiency development after 2020 [6]. It is required to consider the holistic approach comprising the whole energy system in order to achieve energy consumption reduction targets. Such an approach should include DSM, technological solutions, economic and environmental issues, as well as consider user participation in efficient energy consumption. In order to reach the main target – sustainability of the energy sector – systems approach is required for DSM integration that should be ensured at each energy consumption level, starting with the households and ending with the municipality and state levels.

Increasing energy efficiency is a complex approach towards energy consumption reduction. One of the main challenges here is to find the trade-off or balance between energy consumption reduction and corresponding environmental, economic, social and climate aspects. Often setting up the energy and climate political framework utilizes a so-called "trilemma" prism that combines 3 mutually connected aggregations of aspects. World Energy Council defines energy trilemma as a trade-off between energy security, environmental sustainability and energy availability [7]. Electricity consumption reduction can be implemented through the electricity trilemma that defines interactions and equilibrium between three mutually connected system's elements – electricity consumption, impact on climate change (climate sustainability) and costs balance, as shown in the Figure 1.

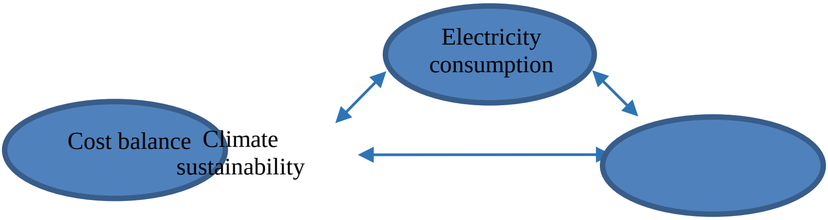

Fig. 1. The trilemma of electricity users

Therefore electricity trilemma serves as a strategy for sustainable DSM integration allowing to bind all the three DSM elements. In the households sector, DSM represents „a key" to energy efficiency improvements. Such a system is based on the households, which influence total costs with their energy consumption habits. The more you use, the more you pay, and vice versa. Through the changes in users' behavior, habits and use of electric/electronic devices, households gain economic benefits from energy savings. In turn, economic benefits would positively influence households, as the financial benefits can be spent on other needs. It is known that climate change poses the effects not only on environment, but also on human. Heat waves affect human health and cause more frequent death cases. Agricultural development and crop growth may be interrupted, leading to food products deficit and increase of food costs.

Natural disasters resulting from climate change directly impact the households. Thus, CO_2 emission reduction can bring economic benefits to the households. At the same time, economic prosperity of the households may influence their decisions and motivation towards emission reduction. For instance, if households have more financial resources, they may be willing to implement and use more innovative and environmentally friendly technologies, which reduce consumption. As electricity consumption goes down, also CO_2 emissions decrease. Consequently, impact on climate change is mitigated. As a result, environment gets cleaner and safer for human health. Nowadays, struggle for CO_2 emissions and its negative consequences reduction creates enormous costs not only at the global and country level, but also at the individual level. Therefore consumption reduction, economic benefits and CO_2 emission reduction form a tight threefold connection.

In the frame of this PhD thesis, electricity consumption of the household sector is studied based on the research of preconditions of DSM implementation at the household level. By introducing DSM, the main goal is to improve energy efficiency and energy consumption reduction in the households.

GOALS AND TASKS OF THE WORK

The goal of this PhD thesis is to develop and approbate preconditions for the implemntation of DSM in the household sector, which is based on electricity consumption data analysis and facilitation of energy efficiency improvements in the households. In order to achieve the goal, the following objectives are set:

• assessment of electricity consumption in the household sector and current situation analysis in the EU and Latvia, determining factors that influence electricity consumption and evaluating future forecasts;

• assessment of smart metering system effect on electricity consumption reduction;

• to analyze electricity consumption in the households using different data analysis methods:

1)regression and corelation analysis;

2)evaluation of smart meters influence;

3)evauation of CO_2 reduction;

4)evaluation of user behavior using Markov Chain theory;

5)development and analysis of electricity consumption profile;

• to determine a benchmark for electricity consumption in the household sector based on analysis of electricity consumption profile;

• to perform the modeling of energy efficiency measures in the households.

METHODS AND STRUCTURE OF THE WORK

The current PhD thesis is based on the analysis of electricity consumption in the household sector and application of different methods for data analysis that is prerequisite for the integration of DSM in the households. Scientific research of this work is based on the aforementioned trilemma of electricity users, and the structure of research methodology is sown in Figure 2.

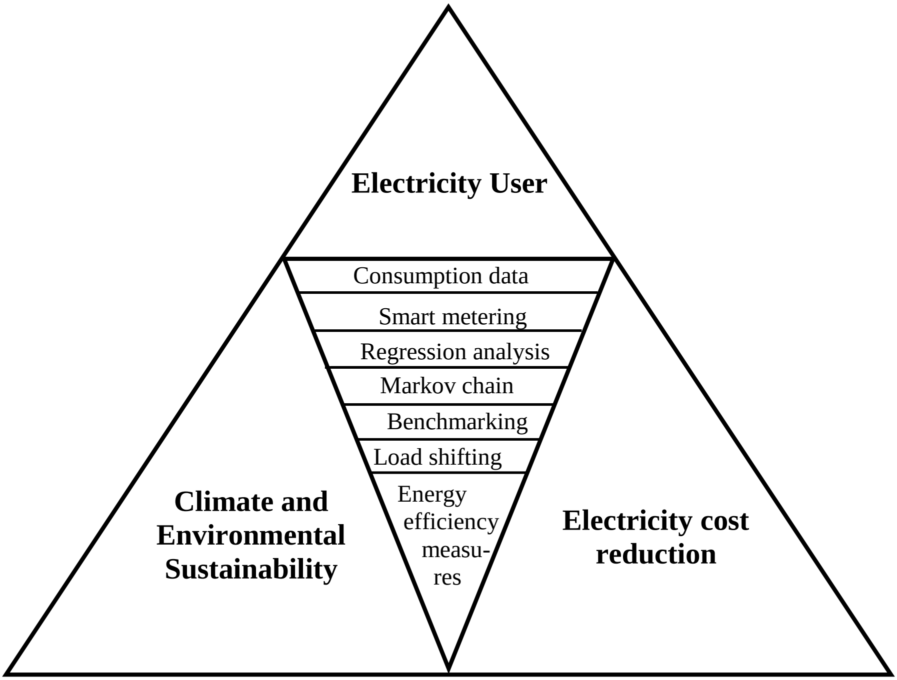

Fig. 2. The overall structure of dissertation methodology

The aim of scientific data analysis is to perform preliminary research on DSM implementation in order to achieve:

- final electricity consumption reduction;
- climate and environment sustainability due to the GHG emission reduction;
- cost balance that is based on economic benefits from electricity consumption reduction.

Various consumption data analysis methods are used in the thesis, resulting in evaluation of factors influencing consumption in Latvia, assessment of smart meters influence on consumption reduction, assessment of influence of users' behavior on changes of consumption, as well as modeling of energy efficiency improvements. In the frame of PhD thesis various data analysis models are developed, which are based on the both – quantitative and qualitative scientific methods. Developed models are approbated on the case study of the first smart meters pilotproject in Latvia "Promotion of energy efficiency in households using smart technologies" launched by JSC „Latvenergo" in 2013, April 1st.

Quantitative data is based on statistical information about electricity consumption of the households of the target and control groups both before pilotproject implementation and during the pilotproject. Data derived from the household survey and questionnaires provides the information on the users' personal, socio-economic and demography aspects, as well as information about the number of electric devices used in households and structural data of the households (type of a building, year of construction, heating system, etc.). Qualitative data is also derived fom the survey and it characterizes households' behavior when using devices, as well as users' attitude towards consumption reduction. The analysis of the current situation in the households, assessment of consumption influencing factors and evaluation of smart metering influence is performed based on statistical analysis of the mentioned data using regression analysis, allowing to define empirical equations. Data gathering, processing and analysis is performed mainly with the help of *MS Excel* environment and *Statgraphics Centurion XVI* softwares. Calculation of CO_2 emission reduction is based on comparison of consumption data before and after implementation of the pilotproject

In the framework of the work, innovative approach is developed, which allows for evaluation of influence of users' behavioral aspects on consumption patterns, applying Markov Chain theory. This research is based on analysis of detailed, in-depth interviews with representatives of 30 target group households with the aim to understand how inhabitants' behavior affect consumption. Collected data is used for the development of 3 Markov chain models, as well as for creation of electricity consumption profiles for 4 types of days (working days and weekends, in winter/or autumn and summer). The developed models are analysed from the perspectives of changes in consumption, user activities and end-use of devices within half-hour and hour intervals. Developed Markov chain models allows for forecasting future consumption, based on the current situation. Mean electricity consumption benchmark for the household sector is determined based on the created consumption profiles. Modeling of energy efficiency measures is performed evaluating 2 kinds of energy efficiency measures that were identified as most frequently mentioned ones during the households interviews – implementation of energy effecient lighting (replacing incandescent light bulbs with LED bulbs) and consumption reduction from switching off a devices in a stand-by regime. Modeling resulted in evaluation of electricity consumption reduction and load shifting based on developed electricity consumption profiles.

SCIENTIFIC SIGNIFICANCE

The PhD research resulted in methodology development that serves as a basis for DSM integration into the household sector. DSM is based on electricity consumption trilemma – trade-off identification between energy consumption reduction, mitigation of climate change and cost balance. In the work, electricity consumption in the househols sector is overviewed with a particular focus on DSM importance and further development of energy consumption monitoring (i.e., smart metering systems) for energy efficiency improvements in the households.

ERlectricity consumption reduction is evaluated through the analysis of consumption data analysis, the assessment of influencing factors and the assessment of smart meterinf on achieved savings using empirical regression models. Based on Markov chain theory, users' behavior and its daily influence on consumption is studied. Behavior and activities in the households and resulting electricity consumption over the twenty-four hours is analyzed for 4 typical day-types (working days and weekends in summer and winter/or autum) that lead to creation of household electricity consumption profiles. The developed Markov chain models allow for forecasting electricity consumption in the future. Evaluation of climate change mitigation is conducted through evaluation of CO_2 emission reduction based on consumption reduction in the households within the pilotproject in almost 2 years. Household consumption reduction is evaluated based on modeling of specific energy efficiency measures. Detailed economic assessment of energy efficiency measures is not performed in the current research, however indicative evaluation is given in order to characterize the influence of the modelled measures on consumption reduction.

This PhD thesis is based on complex assessment of household electricity consumption and energy efficiency improvement opportunities determined through development of different models for data analysis and approbation of those models for current situation assessment and future consumption forecasting.

PRACTICAL SIGNIFICANCE

Besides scientific significance, this PhD thesis has intrinsic practical value. In the work household electricity consumption sector is described and analyzed that resulted in the development of different statistical and mathematic models for electricity consumption data analysis. The developed models can be applied to the characterizationof the household sector in general. During the work, it was concluded that there is a significant energy efficiency potential in the Latvian household sector, which can be revealed through implementation of different measures, such as efficient lighting, the use of new, energy efficient devices, increase of user' awareness and behavioral change. Approach towards DSM integration in the household sector is developed in order to facilitate energy efficiency enhancement. DSM is based on consumption data gathering, data analysis with regression and Markov chain methods, assessment of smart meters, creation of household consumption profiles, benchmarking, modeling of consumption reduction, load shifting and peak load reduction due to the implementation of energy efficiency measures.

The results of this work can be practically used for the analysis of the household consumption profile and energy efficiency policy development in the household sector that serves as a basis for DSM strategy creation and integration in the households. Results of this Thesis can be applicable to different target-groups in the household electricity consumption sector:

- policy makers: based on developed models for data analysis, the factors that influence changes in consumption are determined that require particular attention. Modeling results can be

used for the development of different programs for energy efficiency policy instruments to be applied in the households.
The developed models can be used to forecast consumption changes in the sector and set new consumption and energy efficiency targets in the sector;

- electricity supply companies: in the work, an approach for household consumption data analysis is described based on available data and content of information. Models that are developed and analyzed in the work can be used for forecasting household consumption changes in the future, based on which it is possible to predict required changes in the electricity system (for example, whether there is a need for new generating capacity). Scientific data analysis can serve as a basis for smart metering system development in the future;
- households: research results can serve as the informative materials for households' with regard to implementation of energy efficiency measures and evaluation of their effect on electricity consumption reduction.

APPROBATION

The results are discussed and presented at the following conferences:

1. In the Scientific Conference „The 2nd International Conference on Energy and Environment: bringing together Engineering and Economics" with the paper „Markov chain modelling of household activity profiles based on user behaviour analysis: a Latvian case study" – 18-19 June, 2015, Guimarães, Portugal.

2. In the Scientific Conference „The 14th Conference on Applied Mathematics 2015" with the paper „Application of Markov Chain Approach in Simulation and Analysis of Domestic Electricity Consumption in Latvia" – 3-5 February, 2015, Bratislav Slovākia.

3. In the 55th RTU scientific conference, in section „ Environmental and Climate Technologies" with the paper „Reducing Household Electricity Consumption: The Role of Home Appliance Scheduling, Improved Energy Performance and User Behavioural Change" – 14-16 October, 2014, Riga, Latvia.

4. In the 55th RTU scientific conference, in section „ Environmental and Climate Technologies" with the poster „Comparative Multiple Regression Analysis Of Households' Electricity Use In Latvia: Using Smart Meter Data To Examine The Effect Of Different Households' Characteristics" – 14-16 October, 2014, Riga, Latvia.

5. In the 55th RTU scientific conference, in section „ Environmental and Climate Technologies" with the poster „Analysis of electricity user behavior: case study based on results from extended household survey" – 14-16 October, 2014, Riga, Latvia.

6. In the Scientific Conference „ The 5th International Conference Biosystems Engineereing 2014" with the paper "Determinants of Household Electricity Consumption Savings: A Latvian Case Study" – 8-9 May, 2014, Tartu, Estonia.

7. In the Scientific Conference „The 8th WSEAS International Conference on Energy & Environment „Recent Advances in Energy and Environmental management" with the paper „Forecasting electricity consumption based on smart metering case study in Latvia" – 16-19 July, 2013, Rhodes island, Greece.

8. In the Scientific Conference „The European Conference on Smart Objects, Systems and Technologies" with the paper „The Effect of the Flows of Information on Residential Electricity Consumption: Feasibility Study of Smart Metering Pilot in Latvia" – 11-12 June, 2013, Erlangen/ Nurembeg, Germany.

9. In the Scientific Conference „The 4th International Conference „Biosystems Engineereing 2013" with the paper „Assessment of Changes in Households' Electricity Consumption – 9-10 May, 2013, Tartu, Estonia.

10. In the Scientific Conference „The 5th International Conference „Environmental Science and Education in Latvia and Europe: Resources and Biodiversity" with the paper „Energy End Users Behaviour. Research Groups" – 19 October, 2012, Riga, Latvia.

Monography

Blumberga, D., Veidenbergs, I., Valtere, S., Gedrovičs, M., Bažbauers, G., Blumberga, A., Žandeckis, A., Žogla, G., Kalniņš, S., Laicāne, I., Beloborodko, A., Kirsanovs, V., Timma, L., Muižniece, I., Kļaviņa, K., Lauka, D. // Laboratory Works for Students of Environmental Engineering. Vol.2. Riga: RTU publishing house, 2015. p. 118, ISBN 978-9934-10-595-1.

The list of publications based on thesis research

1. Laicane I., Gehsbargs A., Blumberga D., Blumberga A. Markov chain modelling of household activity profiles based on user behaviour analysis: a Latvian case study // *Proceedings of the 2nd International Conference on Energy and Environment: bringing together Engineering and Economics*, Portugal, Guimarães, June 18-19, Vol.xx, No.x, (2015), pp. xx–xx. (accepted for publication, indexed in SCOPUS).

2. Gehsbargs A., Laicane I., Blumberga D., Blumberga A. Application of Markov Chain Approach in Simulation and Analysis of Domestic Electricity Consumption in Latvia // *Proceedings of the 14th Conference on Applied Mathematics, APLIMAT 2015,* Slovakia, Bratislava, February 3-5, Vol. 1, No. 1, (2015), p. 309-326. ISBN 978–80–227–4143–3. (published, indexed in SCOPUS).

3. Laicane I., Blumberga D., Blumberga A., Rosa M. Evaluation of Household Electricity Savings. Analysis of Household Electricity Demand Profile and User Activities // *Energy Procedia,* Vol. xx, No.x, (2015), pp. xx–xx. (accepted for publication, indexed in SCOPUS).

4. Laicane I., Blumberga D., Blumberga A., Rosa M. Reducing Household Electricity Consumption Through Demand Side Management: the Role of Home Appliance Scheduling and Peak Load Reduction // *Energy Procedia,* Vol. xx, No. x. (2015), pp. xx–xx. (accepted for publication, indexed in SCOPUS).

5. Laicane I., Blumberga D., Blumberga A., Rosa M. Comparative Multiple Regression Analysis Of Households' Electricity Use In Latvia: Using Smart Meter Data To Examine The Effect Of Different Households' Characteristics // *Energy Procedia,* Vol. xx, No. x. (2015), pp. xx–xx. (accepted for publication, indexed in SCOPUS).

6. Poznaka L., Laicane I., Blumberga D., Blumberga A., Rosa M. Analysis of electricity user behavior: case study based on results from extended household survey // *Energy Procedia,* Vol. xx, No. x. (2015), pp. xx–xx. (accepted for publication, indexed in SCOPUS).

7. Barisa A., Rosa M., Laicane I., Sarmins R. Application of Low–Carbon Technologies for Cutting Household GHG Emissions // *Energy Procedia*, Vol. xx, No. x. (2015), pp. xx–xx. (accepted for publication, indexed in SCOPUS).

8. Laicane I., Blumberga A., Rosa M., Blumberga D., Bariss U. Development of Methodology for the Assessmentof Changes in Household Electricity Consumption and Calculation of CO_2 Emissions // *International Journal of Global Warming*, Vol. xx, No. x. (2015), pp. xx–xx. (accepted for publication, indexed in SCOPUS).

9. Bariss U., Laicane I., Blumberga D. Analysis of Factors Influencing Energy Efficiency in a Smart Metering Pilot // *Energetika*, Vol. 60, No. 2, (2014), pp. 125-135. ISSN 0235–7208 (published, indexed in SCOPUS and Web of Science).

10. Laicane I., Blumberga A., Rosa M., Blumberga D. Determinants of Household Electricity Consumption Savings: A Latvian Case Study // *Agronomy Research*, Vol. 12, No. 2, (2014), pp. 527–542. (published, indexed in SCOPUS).

11. Laicane I., Blumberga A., Rosa M., Blumberga D., Bariss U. Forecasting electricity consumption based on smart metering case study in Latvia // *Proceedings of the 8th WSEAS International Conference on Energy & Environment „Recent Advances in Energy and Environmental management", Series: „Energy, Environmental and Structural Engineering",* Greece, Rhodes island, July 16-19, 2013, Vol. 13, No. 1, (2013), pp. 148-156. (published, indexed in SCOPUS).

12. Laicane I., Blumberga A., Rosa M., Blumberga D., Bariss U. The Effect of the Flows of Information on Residential Electricity Consumption: Feasibility Study of Smart Metering Pilot in Latvia // *Proceedings of 2013 European Conference on Smart Objects, Systems and Technologies*, Erlangen/Nuremberg, Germany, June 11-12, (2013), pp. 1-9. (published, indexed in IEEE Xplore).

13. Laicane I., Blumberga A., Rosa M., Blumberga D. Development of Methodology for the Assessment of Changes in Household Electricity Consumption and Calculation of CO_2 Emissions // *International Scientific Conference "Environmental and Climate Technologies 2013"*, Latvia, Riga, October 15-16, 2013, Riga: RTU. Institute of Energy Systems and Environment, (2013), pp. 15-15.

14. Laicane I., Blumberga A., Rosa M., Blumberga D. Assessment of Changes in Households' Electricity Consumption // *Agronomy Research*, Vol. 11, No. 2, (2013), pp. 335-346. (published, indexed in SCOPUS).

15. Laicane I., Blumberga A., Timma L., Romagnoli F., Blumberga D. Energy End Users Behaviour. Research Groups // *Proceedings of the 5th International Conference "Environmental Science and Education in Latvia and Europe: Resources and Biodiversity",* Riga, Latvia, October 19, (2012), pp. 24-26.

Other scientific publications

1. Skujevska A., Romagnoli F., Zoss T., Laicane I., Blumberga D. Wind energy versus natural gas in Latvia: policy evaluation with a System Dynamic simulation // *Proceedings of the 2013 International Conference on Energy, Environment, Ecosystems, and Development, Series: „Recent Advances in Energy, Environment, Ecosystems and Development"*, Rhodes island, Greece, July 16-19, (2013), pp. 141-155. (published, indexed in SCOPUS).

2. Blumberga A., Blumberga D., Bazbauers G., Zogla G., Laicane I. Sustainable Development Modelling for the Energy Sector // *Journal of Cleaner Production*, Vol. 63, (2013), pp. 134-142. (published, indexed in SCOPUS).

3. Ziemele J., Blumberga D., Talcis N., Laicane I. Industrial Research of Condensing Unit for Natural Gas Boiler House // *Journal of Environmental and Climate Technologies*, Vol. 10, (2012), pp. 34-38. (published, indexed in SCOPUS).

4. Laicane I., Blumberga A. Ecoinnovation Diffusion in the Building Energy Efficiency Market // *In: Riga Technical University 53rd International Scientific Conference: Dedicated to the 150th Anniversary and the 1st Congress of World Engineers and Riga Polytechnical Institute /* RTU Alumni: Digest, Riga, Latvia, October 11-12, (2012), pp. 151.

5. Ziemele J., Blumberga D., Laicāne I., Talcis N. Industrial Research of Condensing Unit for Natural Gas Boiler House // *In: Riga Technical University 53rd International Scientific Conference: Dedicated to the 150th Anniversary and the 1st Congress of World Engineers and Riga Polytechnical Institute /* RTU Alumni: Digest, Riga, Latvia, October 11-12, (2012), pp. 161.

6. Blumberga A., Blumberga D., Bazbauers G., Zogla G., Laicane I. Sustainable Development Modeling for Energy Sector // *Proceedings of Global and Regional Research on Sustainable Consumption & Production: Achievements, Challenges, and Dialogues Global Research Forum,* Rio de Janeiro, Brazil, June 13-15, (2012), pp. 1-13.

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DISSERTATION OUTLINE

The dissertation consists of the introduction, three main chapters – literature review and analysis, description of the research methods and model approbation, research results and analysis, conclusions, further recommendations and references. The introduction looks at the topicality of the work, the goals and tasks of the research, the research methods, the importance of the results, as well as scientific and practical significance of the work.

Within the dissertation several stages the the research were carried out based on the stated objectives and tasks of the research – improvement of energy efficiency in households. The first capter provides the literature review and highlights the key studies on household electricity consumption in the EU, world, and Latvia. This part includes an explanation of the factors influencing consumption, analyzes the prerequisites for the implementation of DSM, gives the review of consumption monitoring and smart metering systems and their impact assessment of the decline in consumption, as well as the description of the first smart metering pilot project In Latvia is provided. The second part deals with the examination of the main data analysis methods, description of model development and presents the research results based on model approbation using smart metering pilotproject data. The thirs and forth chapter deals with the evaluation on climate change and CO_2 emission calcualation and the modeling of energy efficiency measures. At the end of the study conclusions and recommendations/suggestions for the future are presented.

The dissertation consists of 183 pages, 4 main chapters, conclusions a bibliography including 49 figures, 18 tables 72 mathematical formulas and equations, 7 appended annexes and a list of references with 326 sources. Literature review is not described in the summary of doctoral thesis.

1. ANALYSIS OF HOUSEHOLD ELECTRICITY CONSUMPTION

1.1. REGRESSION ANALYSIS

There have been number of studies in Europe and worldwide devoted to assessment of factors influencing electricity consumption in the households. In order to evaluate influence of users' socio-economic situation, use of electric devices and other factors. Most typically a statistical method of multi-regression were used [8-23].

Linear multi-regression model for electricity consumption assessment in the households can be described with the following equation [24-27]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p + \varepsilon, \tag{1}$$

where:
Y – the dependent variable;
β_0 – regression function coefficient;
$X_1 ... X_p$ – independent variables;
β_1 – β_p – regression coefficients showing association between dependent variable and independent factors;
ε – error term or noise, that captures all other factors which describes the differences between the variables.

Regression analysis model was approbate on the basis of the JSC „Latvenergo" pilot project data. For the regression analysis the wollowing data are used:

- electricity consumption data for the target and control group in the period form April 1^{st}, 2012 till March 31^{st}, 2014;
- household survey data – the data contain information about households' personal, demohraphic, socio-economic conditions, electric devices being used, awareness of users, their behavior and attitude towads electricity consumption in the household and energy efficiency, as well as data about structural characterstics of the buildings. Survey data were obtained before the start of the pilotproject in the beginning of 2013.

Considering fairly big number of potential independent variables that were available for the assessment of factors influencing electricity consumption, multi-regression model „forward stepwise selection" was used for analysis in order to select only statistically significant factors among the collected variables, which characterize consumption changes in the best fashion [14]. To perform more accurate regression analysis, potential influencing facors were divided into 2 statistical data categories: quantitative data set and qualtative data set. Quantitative data have different nominal or numerical values, for example, (such as household income, number of inhabitants, age of residents, etc. Qualitative data describe the parameter category values (type of building, the gender of respondents, education level, etc.) and binary values (existence of the electrical equipment at home (yes/no), etc.). Qualitative data also describe the user awareness level, users' opinion about electricity consumption and motivating aspects for consumption reduction and energy efficiency improvements in the household. For example, there were several questions in the survey, such as whether resident wishes to receive information on energy efficiency measures, whether energy efficiency measures have been implemented in the household where the responses were yes or no. Electricity consumption and survey data were processed and analysed using *MS Excel* and *STATGRAPHICS Centurion XVI* software.

3 rsegression models was developed based on the 3 research cases:

- 1st regression model: for the assessment of changes in electricity consumption based on target group consumption in the first year of the pilot project implementation and 67 quantitative data;
- 2nd regression model: for the assessment of changes in electricity consumption based on target group consumption in the first year of the pilot project implementation and 23 qualitative data;
- 3rd regression model: for the assessment of factors determining consumption reduction based on electricity consumption savings in the first year of the pilot project implementation and 168 independent quantitative and qualitative variables included in the regression model. Electricity consumption savings were defined as difference between consumption in the period from April 1st, 2012 – March 31st and April 1st, 2013 – March 31st 2014. The „participation group" where titled 1 reflecting participation in the pilot group, and 0 – when participation in the control group, as it is illustrated in the other studies [28, 29].

Based on the equation (1) and 255 number of cases included in the analysis, empirical equation for the 1st regression model was obtained:

$$El = -5044{,}7 + 23{,}2418 \cdot A + 764{,}535 \cdot P + 0{,}0543022 \cdot Inc + 107{,}118 \cdot Y + 53{,}8391 \cdot N_{ee} + 1543{,}84 \cdot N_{es} + 2611{,}5 \cdot N_{eso} + 1860{,}31 \cdot N_{fr} - 475{,}484 \cdot N_{k} - 1316{,}91 \cdot N_{ed} + 2082{,}57 \cdot N_{saun} - 2529{,}21 \cdot N_{vc} + 1291{,}51 \cdot N_{swh} + 1430{,}09 \cdot N_{iwh} + 1235{,}71 \cdot N_{ah} + 947{,}7 \cdot N_{vent} + 384{,}042 \cdot N_{eunderf} + 11295{,}5 \cdot N_{efc} + 549{,}552 \cdot N_{eea} \qquad (2)$$

where:
E – yearly electricity consumption in the target-group househods (from 1st of April 2013 till 31st of March 2014);
A – household area, m^2;
P – household population, number of people;
Inc – households' total net monthly income in previous month after taxes (including scholarships, pensions, benefits, etc.), EUR / year;
Y – age of a respondent, years;
N_{ee} – the number of energy-efficient bulbs, LED bulbs;
N_{es} – the number of electric stoves;
N_{eso} – the number of electric stoves together with an oven;
N_{fr} – the number of fryers;
N_{k} – the number of other kitchen appliances (radio, juice maker, food processor, etc.);
N_{ed} – the number of separate electrical dryers;
N_{saun} – the number of electric saunas or electric bath houses;
N_{vc} – the number of vacuum cleaners;
N_{swh} – the number of storage water heaters (boilers);
N_{iwh} – the number of instant water heaters;
N_{ah} – the number of air humidifiers;
N_{vent} – the number of ventilation equipment;
$N_{eunderf}$ – the number of electrical underfloor heating only in some parts of the house (e.g. bathroom, toilet, kitchen or living room);
N_{efc} – the number of electric firewood chopping devices (an electric chainsaws);
N_{eea} – the number of other electrical equipment used outside of the house.

The multiple linear regression results and overall fit statistics of the 1st regression model (see. the empirical equation (2)) is given in Table 1 (i.e, results from STATGRAPHICS Centurion XVI software).

Table 1

The results of linear regression of the 1st regression model

Parameter	Estimate	Standard error	T-statistic	P - value
CONSTANT	-5044,7	1079,45	-4,6734	0,0000
A	23,2418	2,38586	9,74149	0,0000
P	764,535	141,935	5,38651	0,0000
Inc	0,0543022	0,0243987	2,22562	0,0270
Y	107,118	19,6452	5,45264	0,0000
N_{ee}	53,8391	8,64796	6,22564	0,0000
N_{es}	1543,84	375,964	4,10636	0,0001
N_{eso}	2611,5	517,545	5,04595	0,0000
N_{fr}	1860,31	619,291	3,00393	0,0030
N_{k}	-475,484	97,3118	-4,88619	0,0000
N_{ed}	-1316,91	531,699	-2,4768	0,0140
N_{saun}	2082,57	579,379	3,59449	0,0004
N_{vc}	-2529,21	427,638	-5,91437	0,0000
N_{swh}	1291,51	289,532	4,46067	0,0000
N_{iwh}	1430,09	566,996	2,52222	0,0123
N_{ah}	1235,71	458,615	2,69443	0,0076
N_{vent}	947,7	206,764	4,58348	0,0000
$N_{eunderf}$	384,042	157,388	2,44009	0,0154
N_{efc}	11295,5	1674,16	6,74697	0,0000
N_{eea}	549,552	200,661	2,73871	0,0066

Model Summary and Analysis of Variance					
Source	Sum of Squares	Df	Mean Square	F-Ratio	P – value
Model	$8{,}52578\cdot10^{9}$	19	$4{,}48726\cdot10^{8}$	58,48	0,0000
Residual	$1{,}80312\cdot10^{9}$	235	$7{,}67286\cdot10^{6}$		
Total (Corr.)	$1{,}03289\cdot10^{10}$	254			
R-squared	R-squared (adjusted for d.f.)	Standard Error of Est.	Mean absolute error	Durbin-Watson statistic	Lag 1 residual autocorrelation
82,5429 %	81,1315 %	2769,99	2120,27	1,45603 (P=0,0000)	0,271125

Corelations between measured (observed) electricity consumption and calculated (or estimated) electricty consumption, using regression euqation (2), is shown in Figure 3.

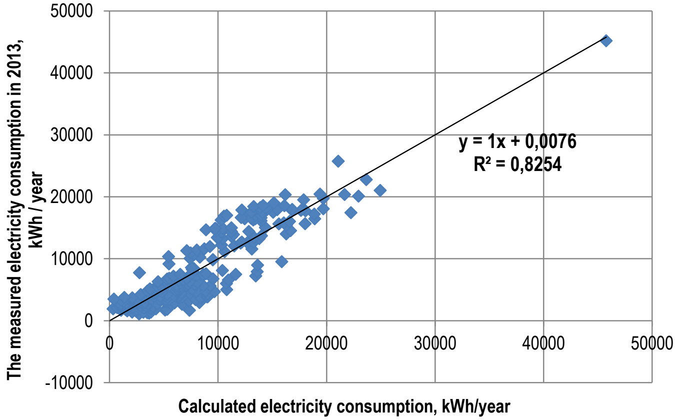

Fig. 3. Correlations between measured and calculated electricity consumption

The corelation coefficient of the 1st regression model (R^2) shows that 19 statistically significant factors included in the model allow to explain 82,54% of changed in electricity consumption. Since the P-value in the ANOVA table is less than 0,05, there is a statistically significant relationship between the variables at the 95,0% confidence level. The obtained research results show that most of the factors have positive impact on consumption, which is consistent with other studies, i.e., with the increase of building area [8-9, 11-15, 17-20, 22-23, 28-50] larger population [8-9, 11-18, 30-34, 43-47, 51-56] larger income [8-9, 11-15, 21, 28-43, 51-55, 57-67], increasing age [11, 14, 19, 30, 33, 37, 40, 42, 44, 45, 47, 68], the existence of electrical heating systems [11, 16, 22, 45, 46, 67, 69-71], electric ovens with or without oven [14, 19, 45, 46, 57], electrical saunas [69] electrical water heating systems [12, 14, 16-19, 28, 29, 45, 69, 71], the electricity consumption increases. Air humidifiers, ventilation equipment and energy-saving bulb have a statistically significant positive relationship between consumption, which differs from the conclusions found in other studies [11, 14-15, 17, 53]. From the results of the 1st regression model it is clear that the tumble dryers and vacuum cleaners have a statistically significant negative impact on consumption, which is in contrast to other studies (for clothes dryers [12, 14, 15, 17, 19, 28, 29, 45 , 57, 69] and vacuum cleaners [45] where the positive impact on consumption changes were observed). Fryers, electric firewood chopping devices and other electrical equipment used outside of the house have a statistically significant positive effect, but other kitchen appliances – a statistically significant negative effect on the changes in consumption**.** The statistically significant impact on consumer changes of these specific electrical appliances have not been studied in directly, therefore these results of the 1st regression model can not be compared with other studies. In general, households with larger area, income, residents' age, higher number of electric devices (particularly, air humidifiers, energy-saving bulb, fryers, electric firewood chopping devices and other electrical equipment used outside of the house and the high-power equipment – ventilation equipment, electric ovens, electrical heating systems, electrical saunas and electrical water heating systems) consume more electricity. Other factors, which characterize amount of different electric devices in the household (the tumble dryers, vacuum cleaners, other kitchen appliances) have a negative influence on consumption changes. Considering the scarcity of information about how inhabitants use those devices, it is necessary to conduct more detailed analysis of user' behavior in order to characterize statistical significance of influence of these factors.

Based on equation (1) and 351 number of cases included in the analysis, empirical equation for the 2nd regression model was obtained:

$$E = 16918{,}2 - 1758{,}39\cdot G + 5061{,}7\cdot T - 970{,}701\cdot N_{LED} - 1292{,}93\cdot A_{LED} - 1367{,}09\cdot S_{stand\_by} - 1648{,}89\cdot M_{reduce} - 2918{,}31\cdot I_{EE} + 2744{,}91\cdot I_{tec} - 4125{,}28\cdot I_{cfdas} \quad (3)$$

where:

G – gender of the respondent;

T – type of a household (private house or apartment);

N_{LED} – LED bulbs are mainly used in the household;

A_{LED} – the respondents' are well aware on advantages of energy-efficient light bulbs and LED bulbs in comaprision with incandescent lamps;

S_{stand_by} – people always switch off electrical appliances from standby mode;

M_{reduce} – the possibility to reduce the costs of consumed electricity is the motivation for enegy efficiency:

I_{EE} – there is interest for users to receive information about energy efficiency measures;

I_{tec} – there is interest to receive comparative information about typical (mean) electricity consumption in the households with similar electricity consumption range;

I_{cfdas} – there are insulated cellar, floor, doors, attic, sealed windows in the household;

Corelations between measured and calculated electricity consumption, using derived regression euqation (3), is shown in Figure 4. The multiple linear regression results and overall fit statistics of the 2nd regression model (see. the empirical equation (3)) is given in Table 2. The corelation coefficient of the 2nd regression model (R^2) shows that 9 statistically significant factors icluded in the model explain 40,87% of electricity consumption changes. Since the P-value in the ANOVA table is less than 0,05, there is a statistically significant relationship between the variables at the 95,0% confidence level.

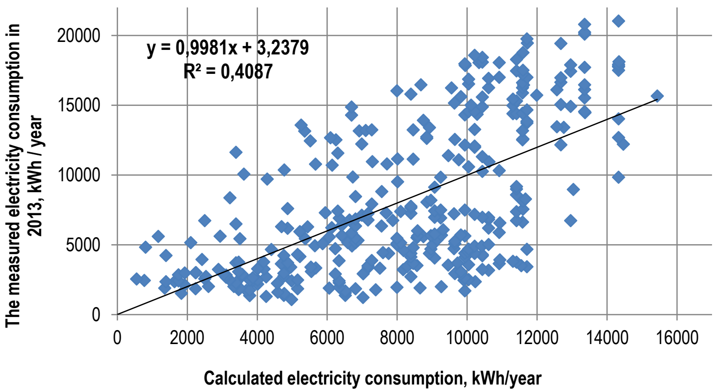

Fig. 4. Correlations between measured and calculated electricity consumption

Table 2

The results of linear regression of the 2nd regression model

Parameter	Estimate	Standard error	T- statistic	P - value
CONSTANT	16918,2	3068,57	5,51337	0,0000
G	-1758,39	475,02	-3,70173	0,0002
T	5061,7	534,764	9,46529	0,0000
N_{LED}	-970,701	318,006	-3,05246	0,0024
A_{LED}	-1292,93	497,477	-2,59897	0,0098
S_{stand_by}	-1367,09	395,257	-3,45872	0,0006
M_{reduce}	-1648,89	478,224	-3,44794	0,0006
I_{EE}	-2918,31	570,475	-5,11558	0,0000
I_{tec}	2744,91	543,145	5,05374	0,0000
I_{cfdas}	-4125,28	1165,36	-3,53991	0,0005

Model Summary and Analysis of Variance					
Source	Sum of Squares	Df	Mean Square	F-Ratio	P – value
Model	$4{,}23265\cdot10^{9}$	9	$4{,}70294\cdot10^{8}$	26,27	0,0000
Residual	$6{,}08579\cdot10^{9}$	340	$1{,}78994\cdot10^{7}$		
Total (Corr.)	$1{,}03184\cdot10^{10}$	449			
R-squared	R-squared (adjusted for d.f.)	Standard Error of Est.	Mean absolute error	Durbin-Watson statistic	Lag 1 residual autocorrelation
40,87%	39,459%	4230,77	3469,74	0,795813 (P=0,0000)	0,597153

This scientific data analysis shows that the larger the household (i.e., private house) and if more household wants to receive comparative information about typical (mean) electricity consumption in the households with similar electricity consumption range, the greater electricity consumption. Also other studies found that higher consumption is in the private houses if compared wit apartments [11, 13-15, 19, 23, 30, 32, 33, 35, 39-41, 44, 45, 49, 50]. According to the results of the 2nd regression model, other facors cause negative influence on consumption changes – if a respondent is female, if LED bulbs are mainly used in the household, if the respondents' are well aware on advantages of energy-efficient light bulbs and LED bulbs, people always switch off electrical appliances from standby mode, if wants to reduce the costs of consumed electricity, if wants to receive information about energy efficiency measures and if more households with insulated cellar, floor, doors, attic, sealed windows in the household – meaning, that consumption is decreasing. These results coincide with the findings of other studies – women are more prone to save electricity [72-76], the higher the level of insulation of the building, the lower the power consumption [14], the more people are aware of the possibilities for reducing energy consumption, the more they are motivated to reduce it [43, 73, 77-80], the more people purchase and use energy-efficient appliances, the less the consumption [14, 18, 19, 21, 31, 37, 43, 67, 77, 81], if more LED bulbs used and if more users are aware of the benefits of LED lamps, the lower the total electricity consumption [11, 12, 81].

Empirical equation of the 3rd regression model (includes 348 number of cases of target and control group households) describing factors determining electricity consumption savings is the following:

$$E_{savings} = 809{,}336 + 331{,}761\cdot Gr + 176{,}549\cdot N_{cm} - 464{,}125\cdot N_{k} + 299{,}506\cdot N_{pc} + 327{,}643\cdot N_{Table\_pc} + 891{,}037\cdot N_{iwh} - 892{,}334\cdot E_{eg} + 472{,}703\cdot N_{saun} + 2241{,}58\cdot N_{sol} + 128{,}405\cdot N_{CRT} - 177{,}651\cdot N_{ac} + 422{,}292\cdot N_{eg} + 2{,}83176\cdot A + 994{,}207\cdot N_{peh} + 900{,}579\cdot E_{heatp} - 1406{,}28\cdot E_{wsh} + 774{,}831\cdot EB + 3509{,}59\cdot E_{airheatp} + 1816{,}02\cdot E_{solc} \quad (4)$$

where:
$E_{savings}$ – electricity consumption savings in 2013, kWh;
Gr – participating group (target or control group);
N_{cm}– the number of coffee machines;
N_{pc} – the existence of the portable computers (pc) in the household;
N_{Table_pc} – the existence of the Tablet PC in the household;
E_{eg} – the existence of the electric gates in the household;
N_{sol} – the number of solariums in the household;
N_{CRT} – the number of analogue TV sets (a cathode ray tube (CRT)) in the household;
N_{ac} – the number of Air conditioning systems in the household;
N_{eg} – the number of electric gates in the household;
N_{peh} – the number of portable electric heaters (oil radiators, thermal ventilators, infrared heaters, etc. space heating devices used in case if getting colder) in the household;
E_{heatp} – the existence of the geothermal heat pump (Ground source heat pump) in the household;
E_{wsh} – the existence of the water source heating system in the household;
EB – the existence of the electrode boiler in the household;
$E_{airheatp}$ – the existence of the air heat pump in the household;
E_{solc} – the existence of the solar collectors in the household.

Corelation between measured and calculated electricity savings using the obtained regression equation (4) is shown in Figure 5. The multiple linear regression results and overall fit statistics of the 3rd regression model (see. the empirical equation (4)) is given in Table 3. The corelation coefficient of the 3rd regression model (R^2) indicates that 15 factors included in the mode let explain 63,35% of electricity consumption savings. In overall, the results of a scientific research show that smart meters have statistically significant influence on electricity consumption reduction, and higher savings have been achieved in a target group, compared to the control group.

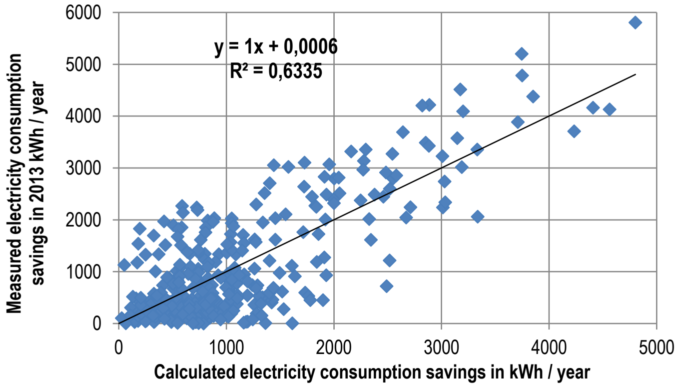

Fig. 5. Correlations between the observed and estimated electricity savings

Table 4

The results of linear regression of the 3rd regression model

Parameter	Estimate	Standard error	T- statistic	P - value

CONSTANT	809,336	180,721	4,47836	0,0000
Gr	331,761	76,7802	-4,32092	0,0000
N_{cm}	176,549	82,2051	2,14767	0,0325
N_{k}	-464,125	122,377	-3,7926	0,0002
N_{pc}	299,506	96,5475	3,10216	0,0021
N_{Table_pc}	327,643	86,3992	3,79219	0,0002
N_{iwh}	891,037	134,795	6,61033	0,0000
E_{eg}	-892,334	201,554	-4,42727	0,0000
N_{saun}	472,703	140,054	3,37514	0,0008
N_{sol}	2241,58	546,113	4,10461	0,0001
N_{CRT}	128,405	33,3872	3,84594	0,0001
N_{ac}	-177,651	65,6817	-2,70472	0,0072
N_{eg}	422,292	130,97	3,22434	0,0014
A	2,83176	0,342475	8,26852	0,0000
N_{peh}	994,207	188,343	5,2787	0,0000
E_{heatp}	900,579	130,065	6,92408	0,0000
E_{wsh}	-1406,28	696,249	-2,01979	0,0442
EB	774,831	246,986	3,13714	0,0019
$E_{airheatp}$	3509,59	487,09	7,20521	0,0000
E_{solc}	1816,02	359,341	5,05376	0,0000

Model Summary and Analysis of Variance					
Source	Sum of Squares	Df	Mean Square	F-Ratio	P – value
Model	$2{,}61374 \cdot 10^{8}$	19	$1{,}37565 \cdot 10^{7}$	29,84	0,0000
Residual	$1{,}51234 \cdot 10^{8}$	328	461079		
Total (Corr.)	$4{,}12608 \cdot 10^{8}$	347			
R-squared	R-squared (adjusted for d.f.)	Standard Error of Est.	Mean absolute error	Durbin-Watson statistic	Lag 1 residual autocorrelation
63,35%	61,22%	679,028	516,417	1,92759 (P=0,2501)	0,0355323

The results of the empirical equation (4) shows that statistically significant positive impact on consumption savings result from participating group (if the household belongs to a target group), building area, coffee machines, laptop andf tablet computers, saunas, solariums, CRT televisions, electric gates, portable electgrical heaters, ground heat pumps, air heat pumps, the electrode boilers and solar collectors. It means that, if these parameters increase, electricity consumption savings are higher. Some of these factors coincide with other studies – if households belong to the smart metering group [9, 28, 29, 43, 77, 82-109], if the hosehold area is higher [77, 81] if there are electric water heating [178] and if more energy efficient technologies, including solar energy technologies, are used [14, 18, 19, 21, 31, 37, 43, 67, 77, 81 – it lead to consumption savings. On the other hand, if there are more other kitchen appliances, the existence of electrical gates, air conditioning systems and the existence of the water source heating system, then savings are smaller. Regarding air conditioners, other studies fond that their use, especially during the summer season, increases consumption [12, 16, 17, 21, 31, 37, 41, 52, 70, 71].

1.2. MARKOV CHAIN MODELS

The doctoral thesis presents a novel approach for analysis of the behaviour of household inhabitants and for modelling and prognosis of their electricity consumption, based on Markov chain theory. The household electricity consumption profiles are analysed through the developed Markov chain models. The summary of doctoral thesis does not provide in detail description of

Markov chain theory, the foundation of Markov chain process modelling or description of the mathematic formulas that are used to develop three Markov chain models in detail. In the following a short description of Markov chain theory and the generic formulas is provided. The detail description is provided in chapters 2.3. and 2.4. of the doctoral thesis.

Markov chain is an approach for modelling of the probability of future prognosis and forecasting. This approach allows to develop descriptive model of random events in discrete time steps (events are observed at certain points in time), where the past events impact the future based only on the present state of the system [110]. Markov chain is defined as "an approximation of the chain of independent attempts and it is based upon the hypothesis that the dependence of the results of the n + 1 attempt is expressed only through the result of nth attempt" [111-113]. Corresponding model is based on the identification of probabilities of systems transition from one state to another. Even though all previous states of the system are known, the system is dependent only on the specific state at which the system is at the n – 1 step [113]. If random values are given by integer numbers, they can be recorded as the series of S elements or series as {Xn}n≥0, where Xn=j, if the event Ej has taken place during the nth attempt, then this string {Xn}n≥0 forms the Markov chain, which can be recorded with the following equation [111-113]:

$$P(X_n = j \mid X_0 = k_0, X_1 = k_1, ..., X_{n-2} = k_{n-2}, X_{n-1} = i) = P(X_n = j \mid X_{n-1} = i) =: p_{ij}^{(n)}, \sum jp_{ij}^{(n)} = 1, \quad (5)$$

where:

$p_{ij}^{(n)}$ – probability of the transition from state i to state j during the nth modelling step;

i and j – event transition states;

k – discrete time period.

The Markov chain model begins with a given distribution of the initial states in the following form [111, 113]:

$$P(X_0 = j) = p_j^{(0)}, \sum jp_j^{(0)} = 1, \ j = 1,2,.... \quad (6)$$

In any case, the condition that the sum of the probabilities of Markov chain states is 1 is fulfilled and can be written in the following form [111-115]:

$$\sum\nolimits_{i=1}^{n} p_i = 1. \quad (7)$$

In order to conduct Markov chain process, it is important that the Markov property, expressed by the following equation, is fulfilled [112, 113]:

$$P(X_n = k_n \mid X_0 = k_0, ..., X_{n-1} = k_{n-1}) = \frac{p_{k0}^{(0)} \cdot p_{k_0 k_1}^{(1)} ... p_{k_{n-1}k_n}^{(n)}}{p_{k0}^{(0)} ... p_{k_{n-2}k_{n-1}}^{(n-1)}} = p_{k_{n-1}k_n}^{(n)} = P(X_n = k_n \mid X_{n-1} = k_{n-1}) \quad (8)$$

where:

$p_{k0}^{(0)}$, $p_{k_0 k_1}$, $p_{k_{n-1}k_n}$ – probability distributions, which are independent of each other.

Transition probability matrix P is described by the changes in the system after each modelling step, but for real systems the modelling is performed based on a number of potential steps in the system denoted as k. In this case, the transition probability for k steps is described as $p_{ij}(k) := P(X_k = j|X_{k-1} = i),\ k \geq 0,\ i,j \geq 1$. The sum of the probabilities of Markov chain states is equal to 1 ase recorded by equation (7). The equation for the resultant distribution of probabilities of all events is expressed by the following relationships [110, 111, 113]:

$$p_{ij}(k) = \sum_S P(X_{k-1} = s|X_0 = i)P(X_k = j|X_{k-1} = s) = \sum_S p_{is}(k-1)p_{is}. \tag{9}$$

and

$$P(X_0 = i_0, X_1 = i_1, X_2 = i_2, ..., X_n = i_n) = \mu(i_0) \cdot p_{i_0,i_1}(0,1) \cdot p_{i_1,i_2}(1,2) \cdot ... \cdot p_{i_{n-1},i_n}(n-1,n), \tag{10}$$

where:
$\mu(i)$ – the initial states distribution function.

If the Markov chain involves a series of uniformly distributed, mutually independent, random, time dependent variables, then the Markov chain is described by the transition probabilities shown in the equation (11) [11]:

$$p_{ij} = P(X_n = j|X_{n-1} = i), \tag{11}$$

and the following transition probability matrix P [111, 113]:

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix}, \tag{12}$$

where:
$p_{11};\ p_{11}\dots$ – describes the probability of the transition from state 1 to state 1, describes the probability of the transition from state 1 to state 2 etc.;
P – the matrix for probability of transition for these states or transition matrix $P(m, n)$.

Similarly as the sum of the probabilities of Markov chain states is 1, the sum of matrix element rows is equal to 1.

1.2.1. THE RESULTS OF CONSUMPTION MODELLING

The „Consumption model" is developed based on the Markov chain theory by using data about electricity consumption profiles for 315 households for the time period from April 1st, 2013 until March 31st, 2014. Four „typical" types of days were analysed: summer day (July), autumn day (October), as well as, working days and weekends. Consequently, separate models were developed for each season. The available data for half-hour electricity consumption indicates both very small (0 kWh) and very large (up to 10-12 kWh) consumption and the distribution of consumption has the presence of "heavy tail". Therefore distribution of decimal logarithm of consumption was considered, providing the advantage that the consumption is estimated as the average value of decimal logarithm and not as a simple average consumption value. Decimal logarithm i.e. distribution of log10(w) improves the existing data distribution by identifying a better average consumption profile from the given dataset. Such distribution is visibly symmetrical and allows more detailed observation. This approach reduces the possibility, that large size households (i.e., those, hwo consume large amount of electricity in month) can have important influence on the result of prognosis. Based on such distribution twenty states of the Markov chain were created, where the first state accounts for levels of minor consumption and the last state describes the highest levels of consumption. Based on such distribution we have created twenty states of the Markov chain, the first state accounting for minor levels of consumption and the last one – describing highest levels. Bins for the states were chosen as 20 quantiles of the distribution of decimal logarithm of consumption (5% quantile, 10% quantile, etc.):

First state average consumption $w < 0.0002$ kWh
Second state average consumption $0.0002 \leq w < 0.069$ kWh.
Third state average consumption $0.069 \leq w < 0.11$ kWh.
....
Nineteenth state average consumption $2.14 \leq w < 2.69$ kWh.
Twentieth state average consumption $w \leq 2.69$ kWh.

Based on the equation (12), the state transition probability matrix for the "Consumption model" is described as:

$$P = \begin{pmatrix} p_{1,1(k)} & p_{1,2(k)} & \cdots & p_{1,20(k)} \\ p_{2,1(k)} & p_{2,2(k)} & \cdots & p_{2,20(k)} \\ \vdots & \vdots & \ddots & \vdots \\ p_{20,1(k)} & p_{20,2(k)} & \cdots & p_{20,20(k)} \end{pmatrix}. \tag{13}$$

For this Markov model a 20 x 20 state transition matrix was defined for each time step (half-hour). Each $p_{ij}(k)$ element of the matrix characterizes the probability that electricity consumption will change from state i to state j during the time step from k to k+1. Twenty-state Markov chains were constructed for working days and holidays separately for autumn and summer (matrix for autumn was estimated based on October data and for summer based on July data). As transition probabilities change substantially during the day, non-stationary Markov chain model was applied for 4 combinations of day types. For every type of the day and season 48 Markov matrices were estimated showing the transition probabilities for t = 00:00, t = 00:30, ... , t = 23:30. Total number of estimated matrices is $48 \cdot 4 = 192$ (total of 48 matrices for each pair weekday/holiday and summer/autumn).

The states of the Markov chain were identified all day long and used to calculate the estimated average consumption of a total of 1000 simulated households. The predicted average values are calculated using equations (14) and (15):

$$\bar{l}(t) = \sum_{k=1}^{20} p_k(t) l_k, \tag{14}$$

$$\overline{w}(t) = 10^{\bar{l}(t)}, \tag{15}$$

where:
k – the state of Markov chain;
t – discrete time intervals (changes from 00:00 to 23:30) with the step of half hour;

$p_k(t)$ – a proportion of those households that t are at the state k at the given time interval in relation to the total number of simulated households (in total, 1000 households);
l_k –the average value of decimal logarithm of consumption for k-th state;
$\overline{w}(t)$ – electricity consumption, kWh.

The results of the modeled electricity consumption and the real consumption profile (based on empirical data), as well as, the deviance between modeled and real time series for working days and holidays in autumn season are presented in Figures 6 and 7, but for summer in Figures 8 and 9.

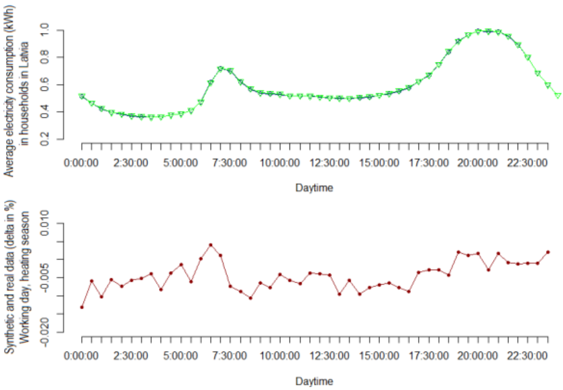

Fig. 7. Upper graph: modeled (green triangles) and real (dark blue circles) averaged profiles (working day, heating season). Lower graph: deviance between modeled and real average electricity consumption profiles (in %)

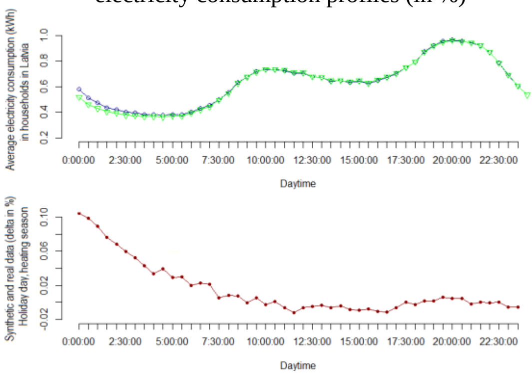

Fig. 7. Upper graph: modeled (green triangles) and real (dark blue circles) averaged profiles (Holiday day, heating season). Lower graph: deviance between modelled and real average electricity consumption profiles (in %)

The obtained results indicate that the electricity consumption profiles for modeled and real data for both seasons look similarly. Small differences may be indicated. The results show that the average consumption profile and the modelled profile for working days in October (Fig. 6, upper graph) are practically overlapping, and the error between the simulated and the real profiles are less than 1% (Fig. 6, lower graph). The results for October holiday consumption profile (Fig. 7, upper graph) the Markov model shows a slightly lower consumption profile at the initial stage of the modelling of the holiday (at approximately 00:00). This initial deviance for holuiday during autumn occurs most likely due to choice of the initial state of the Markov chain. Such initial state is chosen via distribution of households among the states at 00:00 o'clock that were estimated through all empirical data. The results of the modelling show that even if the initial state is chosen wrongly, during the next steps the Markov model is adjusting its results to the real consumption profile. The difference in the errors (Fig. 7, lower graph) shows that, taking into account the initial state difference between the real and the modelled profiles, the error between the two profiles is larger (slightly above 1%). Error decreases with time due to the adjusting of the modelled profiles.

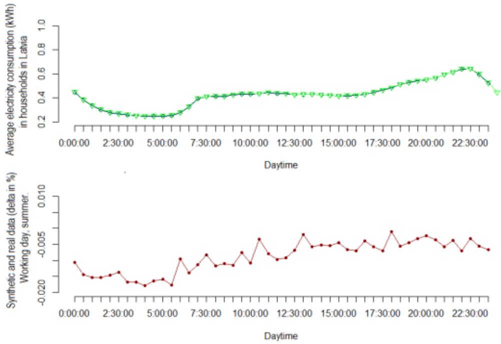

Fig. 8. Upper graph: modeled (green triangles) and real (dark blue circles) averaged profiles (Working day, summer). Lower graph: deviance between synthetic and real average electricity consumption profiles (in %)

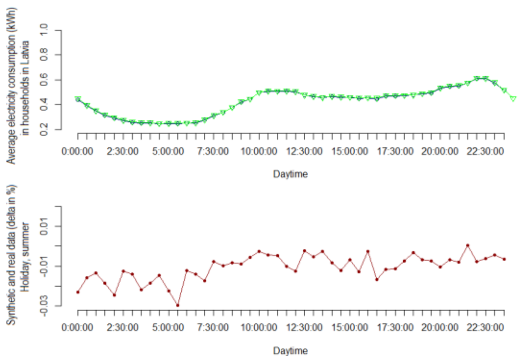

Fig. 9. Upper graph: modeled (green triangles) and real (dark blue circles) averaged profiles (Holiday, summer). Lower graph: deviance between synthetic and real average electricity consumption profiles (in %)

Similar conclusions can be made about the modeled and real consumer profiles for summer time (see. Fig. 8-9). However, the results for summer season show that the modelled and the real electricity consumption profiles for summer season are slightly more accurate, with smaller margins of error then in case of heating season days. This can be explained by the fact that during the summer the daily consumption profile is less stochastic and hence more accurate

Markov chain modelling can be performed. Comparing the real and simulated electricity consumption profiles, the differences between the obtained results are less than 1% for all types of data and all day combinations. Moreover, even if initial states of the households are known with error, such error converges to sustainable level during simulation. In addition we can conclude that Markov chain is a suitable approach for simulating „standard" profile with high precision.

To verify that the Markov model can be used to model the behaviour of the same consumers in different seasons, the electricity consumption profile for April was modelled using the previously described October transition matrices. This test is called cross validation or out-of-sample testing in order to check if the model could be applied to simulate performance of the same consumers during other seasons. That is, we simulated average monthly profile using Markov chain for autumn and compare the profile with real average profile for April. Here real consumption was averaged over 315 households for every day of October and every half-hour period. The simulation results are shown in Figures 10 and 11.

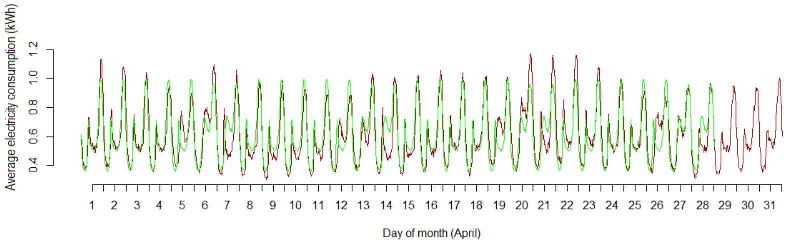

Fig. 10. Dynamics of modelled (green) and real (red) consumption for April 2013

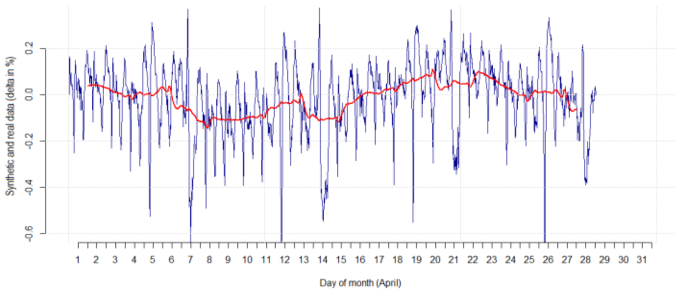

Fig. 11. Dynamics of deviance between synthetic and real data for April 2013

In this case, larger deviance is observed between modeled and real data. Reported differences between the modelled and the real data are greater (within range of ± 10%, see Fig. 11). From the research results follows that the Markov chain that has been developed for working days in October, can provide moderate accuracy for modelling of working day profile in April (see Fig. 10). Consequently, if the October Markov chain states would be applied for modelling of April holiday forecasts, the accuracy would be even lower. Therefore, to achieve a higher accuracy, Markov chains should be separately adjusted for each season and type of day. The obtained results show that in most cases the modelled data are overestimated in comparison with real data, because the differences between them were largely negative. This discrepancy arises because the last states of Markov chain influence the average value that has also been observed in other studies [116-141]. The values that are predicted based on the last Markov chain states shows higher consumption forecast and sequentially, the average value is higher. To limit the impact of such problems, more sophisticated division of the highest electricity consumption groups must be chosen.

In general, the only required input data for Markov chain simulations are the household distribution between the Markov chain states at the initial moment of time 00:00, where,all the temporary data being re-created on half-hour time step throughout the month. The transition matrices were identified for four typical types of days – working days in summer / autumn and holidays in summer / autumn. As can be concluded from the results of „Consumer model" the „average" electricity consumption profile can be reproduced with high precision where the average difference between modelled and actual data of Markov chain model did not exceed 10%, but the error for this difference was less than 1%. Additional simulation results (cross-validation) showed that the Markov chain can be used with moderate to high accuracy for predicting monthly electricity consumption also for other months within the error range between the profiles of ± 10%). Moreover, Markov models were capable to simulate cyclical patterns of consumption. However, additional analysis showed that individual Markov chain models should be adapted to every season and type of the day in order to achieve better precision. The developed markov chain model is comparable to other studies [116-141].

1.2.2. THE RESULTS OF ACTIVITY MODELLING

The „Activity model" is based on Markov chain theory and it was developed to further expand the „Consumption model" by analysing the distribution of transition probabilities taking into account the activity level of the household dwellers, e.g., are they active or inactive at certain time step. The aim of the activity model is to evaluate (through application of Markov chain) the impact of the activities states upon the electricity consumption. The "Activity model" is based on survey data about the activity profile of 30 Latvian households. This model includes definition of two Markov chain transition states for each time step (one hour), e.g., if household dwellers are active at the certain time step and they consume electricity or they are inactive and do not consume electricity, where „active" households were denoted by Markov chain state „1", „inactive" households – „0". Sequentially there are four potential probability transition pathways: 0-0, which means that the household is inactive at given time step and will continue to be inactive is the following time step; 0-1, e.g., the household is inactive at given time step, but will be active in the next one, etc. Following, the Markov transition probabilities $P_{ij}(k)$ are determined, where $p_{(0\text{-}0)}$, is the probability that system will transition from zero to zero (0-0) for the next time step etc.

Fig.12 provides the results of the Markov Markov model (average simulated occupancy) for four different types of day that is compared with the average electricity profiles of the 315 households for four typical cases (i.e., the figures show the proportion of active occupants in the households and compared to the average electricity consumption). The results of Markov model are expressed as the share distribution of the activity for each hour (values are expressed in percentage on the left side Y axis), the average electricity consumption profile is presented in kWh (values are expressed in kWh on the right side Y axis).

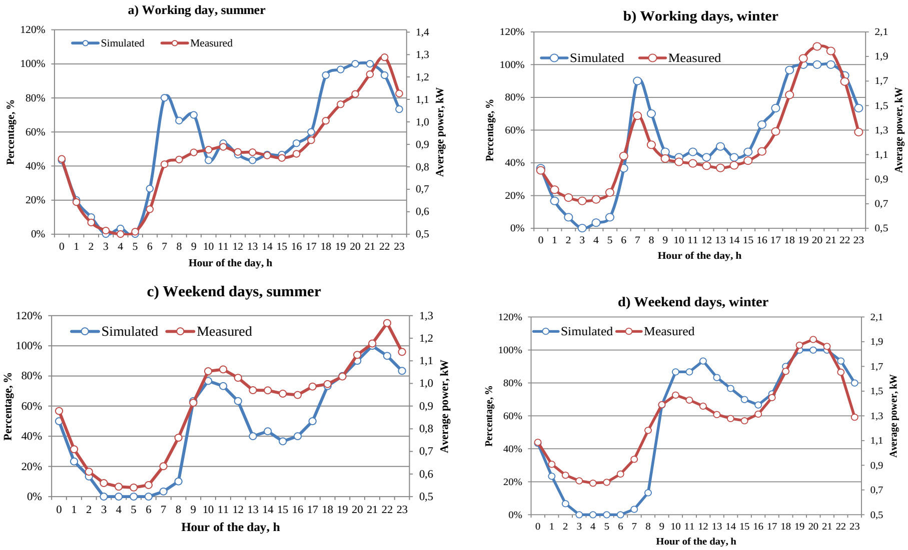

Fig. 12. Modeled and measured household data for four typical types of days: a) working days, summer; b) working days, winter; 3) weekend days, summer; and 4) weekend days, winter

As it can be seen from the modeling results (see Fig. 12) there are differences between modeled household ocupancy activity (obtained by Markov chain) and measured average consumption profile. However the results show that the similar trend are well reproduced by the model and activities are well represented both by Markov chain model and the average profiles. It is clearly seen that if the household is more active at particulal time of the day, it also shows higher rate of electricity use. The modeling also can successfully represent similarities regarding the consumption peaks and their magnitudes. Transitions to an active occupancy state, shown in Figure 12, occur twice: the first peak apperas early in the morning, but the second – later in the evening. The simulation results also show a relatively high transition to the active state in the working days in summer and in the morning hours in the winter. Nevertheless, as the results show, the activity peaks on working days within the Markov model are slightly overestimated in comparison to the average activity profile (see Fig. 12 a) and b) graphs). It can be explained by the user answers that they are active in the morning, but not always associated with sudden growth in consumption. Regarding the summer holidays, it can be noticed, that during daytime and evening hours Markov model results show significantly lower activity than the average consumption profile. The Markov model results for winter holiday midday are more overestimated or shows increased activity compared with the average profile. In general the results of the modelling show that the modeled user activity coincides well with the measured data. The average activity profile shows a similar trend, as described in other studies where greater activity were observed on weekends than on weekdays, associated with a higher level of consumption [120, 123-125, 127, 135]. The analysis shows that not allways the model gives an exact reproduction of the user activities in connection with electricity use. The user activity modeling with Markov chain method showed that the differences between the modeled and real profiles were greater than 10% but are below 30%.

Given the fact that the Markov model was created on the basis of 30 household survey data, the BOOTSTRAP method was used to evaluate the model's prediction capability. BOOTSTRAP method is applied for searching of statistical quantiles, based on which it possible to determine whether to accept or reject the null hypothesis [142-144]. This method allows to evaluate the distribution of the sample data set using a random sample method [143]. The essence of BOOTSTRAP is to construct the relationship between the predicted data sets and sample data sets. It adopts a given sample $X_1, X_2, ..., X_n$ as being a good representative for the generation of new data, and produces BOOTSTRAP sample $X^*_1, X^*_2, ..., X^*_n$ as the realization of new data [142]. Figure 13 shows how the Markov chain could anticipate data when the BOOTSTRAP function is used. One simulation profile – a working day in the summer – is shown as an example.

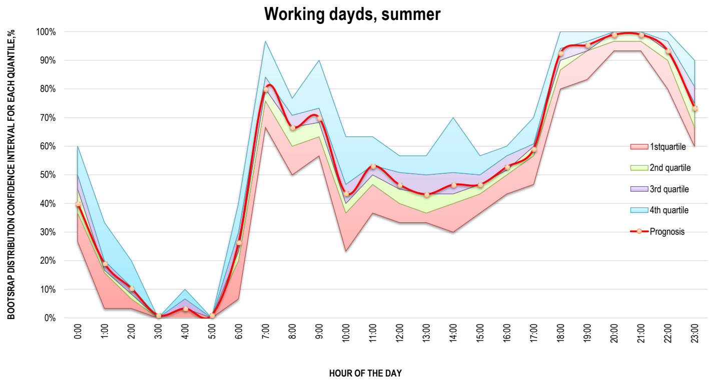

Fig. 13. Markov chain model for prediction using BOOTSTRAP function

The quantile representation shows the maximum probability assessments within the confidence interval, where each quantile is represented in the allowable range of values. Quantile representation is based on the empirical data distribution. 4 quantile areas were adopted, where 1st quantile shows the minimal acceptable probability values, 2nd and 3rd quantile – higher values, but 4th quantile – the maximum permissible values. As it can be seen from the research results, higher probability value differences are observed in 1st and 4th quantile. Modeling prognosis (red line in Fig. 13) can be used to simulate the new data as a set of quantile confidence band does not exceed 18-20%. The simulation results showed that the maximum probability assessment model is asymptotic with a normal distribution, where the forecast is situated in the quantile confidence bands. The results show that the maximum likelihood estimates are normally distributed, so that the null hypothesis can be rejected and the resulting Markov model results are correct at the 95% confidence level.

1.2.3. RESULTS OF APPLIANCE USE MODEL

The „Appliance use model" is based on the 28 Latvian household survey data during the face-to-face interviews. To create this model, consumption diaries were set up where the ise of all electrical appliances on a daily basis is clarified – i.e., what kind of electrical appliances and for how many hours they are used (also the type and power of particular appliances were fixed). Thus, the information collected on the basis of the consumption diaries allows to evaluate the user behaviour on how the resident living in the household use different electrical devices. The Markov states for „Appliance use model” are defined according to the use of electrical appliances and related consumption of a given hour. The patterns of „Appliance use model” were defined as 4 Markov states as shown in Table 14.

Table 4

Definition of Markov states for „Appliance use model”

Markov state	The state name	Markov state limiting values, kWh/hour
0	Base state	-
1	Small consumption	Up to 0,2 kWh/hour
2	Medium condumption	From 0,21 – 1,1 kWh/hour
3	High consumption	Starting form 1,1 and more kWh/hour

The definition of Markov states for „Appliance use model” is based on the calculation of the average consumption that each household consumes at the particular hour. Even if the household is inactive (i.e., do not use electrical appliances), this means that the household use electricity, which is independent of activities and can be defined as the so-called „Base consumption”. Base consumption of each household is different because of different conditions of households and the number of electrical appliances. The level of „base consumption” has no impact on Markov model, because the simulation is designed in order to assess how households move from small to large consumption and vice versa. Based on data provided by the interviews and the calculation of hourly household consumption, the Markov states - base, small, medium or large – were defeined for the households at a particular hours. These activity states were used to generate the Markov chain transition matrices for 24 hour intervals. The Markov chain probabilities and transition change matrix for „Appliance use model” is calculated in a similar manner as for „Consumption model” and „Activity model”. Figure 14 compares the obtained results for „Appliance use model” for a randomly chosen and newly modeled profile, which is compared with the average consumption profile (i.e, based on the average consumption of the 28 households). The results of the Markov chain modelling allows to generate a sufficiently precise household electricity consumption profile, which is similar to the real data. Scientific evidence shows that the modeled data in most cases „overestimate” the electricity consumption, compared to the actual average consumption data for all typical daily profiles. This is because there is a difference between and the modelled values and the average values on the basis of which consumption profiles for 28 households were calculated (i.e., the arithmetic mean of the function average was used, i.e., AVERAGE function in *MS Excel*). The modelled profiles commonly indicate higher values than the average values (similar to findings in other studies [116-119, 137]). Similar to the „Activity model” also in this model, the latter stages of Markov chains have high impact on the average value, and therefore affects the new profile. In McKenna and others study [137] it was concluded that the modeling profiles underestimates consumption values at the beginning of the day, but overestimates the consumption at the end of the day. If you look at the randomly selected household data (see. Fig. 14 blue curve), we can conclude that electricity consumption overestimation is more or less equally expressed in weekdays and weekends.

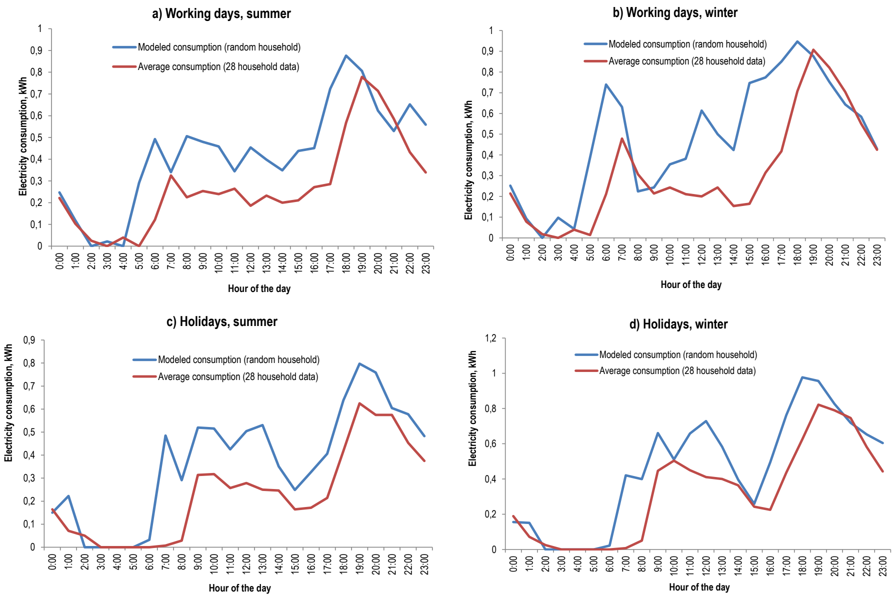

Fig. 14. The modelled profile of one randomly selected household in comparison with the average consumption profile of 28 households for 4 day profile types: a) working days, summer; b) working days, winter; c) holidays, summer; and d) holidays, winter

However, slightly higher overestimation is observed during the summer weekends and weekdays. As can be seen, slightly better simulation results are represented for holiday consumption profile, if compared with working day consumption profile. The evaluation of summer consumption is less accurate, if compared with winter season. In Widén and others study [117] the modeled weekday consumption was underestimated while the holiday consumption showed the overestimation of the modeled data in comparison with the original data. As can be seen (see Fig. 14), the consumption is higher in the evening hours, but the much lower at the night time, since household residents are sleeping (it coincides with other studies [116-120, 123-125, 127, 135]). The higher differences were also observed between weekday and weekend consumption profiles within one season, which corresponds to findings in other studies [118-120, 136]. Consumption level also varies depending on the season (similar to findings in other studies [116, 118, 119]). From the derived results it is evident that the slightly higher total consumption can be observed on weekends than on weekdays – it coincides with the findings of other studies [116, 120, 123-125, 127, 135, 136].

All profiles show three „peak" times of consumption that meets the morning, noon and evening hours, where the evening „peak" is the greatest, due to the increased activity of the users. Such recognition coincides with other studies [124, 127, 136]. As shown by the modelling results, the „peak" consumption for the actual and modeled profiles does not match in time and the difference is usually in the range of 1-2 hours. It is similar to the findings from other studies [126]. For example, on weekdays during the summer real data show that in the morning „peak" consumption takes place around 7:00, while the modeled profile shows that the peak occurs earlier, around 6:00. Also, for weekday evenings in the summer the evening „peak" of real data is around 19:00, but the results of the model „peak" appears around 18:00. In addition, the holiday morning „peak" is smoother and it happens in later holiday morning hours than on weekday hours (similar to the findings found in other studies [116, 124, 136].

Markov chain model results show that if we known how households use appliances at a given hour, it is possible to use markov chain for such user behaviour analysis. Similar to the both models described above, the only necessary input data to Markov chain simulations for the „Appliance use model" is household distribution in the Markov states at the initial moment of time 00:00. Based on that, all consumption data were generated anwe for each hour throughout the day. Modelled results clearly show that consumption profile can be realistically reproduced similar to the existing consumption profile with high precision. Also in this model, the difference between the model and the real data does not exceed 30%.

1.2.4. GENERAL CONCLUSIONS ABOUT MARKOV CHAIN MODELS

To generate new data and develop future electricity consumption prognosis, whitin this doctoral thesis three Markov chain models have been developed based on existing consumption data. All three Markov chain models are compared with the actual electricity consumption data. The „Consumption model" and „Activity model" are compared with an average electricity consumption profile from 315 households, but the „Appliance use model" is based on and compared with data from 28 households. The cross validation test was used for the „Consumption model" in order to evaluate, how precise prediction can be carried out based on an alternative data, i.e., forecasting is done for another consumption period based on particular data for the given month. Cross-validation is a useful method if the data are available for short time period (e.g., one year). Cross-validation is mainly applied for prediction purposes, to evaluate how accurately the model prediction can be applied in practice. This test also enables to evaluate of how the results of statistical analysis can be generalized to another, independent dataset is used. It also allows to assess how the results can be used to forecast consumption for another time period, based on existing data. For this modelling the October data were substituted by April data. The analysis showed that electricity consumption could be sufficiently predicted, based on the exiting data. For the „Consumption model" the precision is assumed to be high enough, i.e., in range of ±10%. Therefore Markov chain can be used for predicting electricity consumption to other month with moderate precision. This means that with this Markov model it is possible to develop future prognosis with qute high precision. For example, if it is possible to simulate existing data with 10% precision, then also the prognosis for the next year (e.g. 2015, 2016 etc.) will be with 10% precision. For the modelling of household dweller activity („Activity model") and the modelling of electrical appliance use („Applianceuse model") the difference between the modelled and real data was larger than 10%, but did not exceed 30%.

This doctoral thesis is one of the first research, where the probabilistic approach has been applied for household electricity consumption data analysis in Latvia. The future research need to be directed towards expanding of the Markov chain model by gathering more specific data about the user activities and their relation to electricity consumption within a larger group of households. The developed models may be supplemented by alternatives for categorizing of various activities. One of the important benefits for future research would be to investigate how Markov chain could be applied for evaluating the energy efficiency potential of specific energy efficiency measures, including, but not limited to, the behavioural change (e.g., turning off the devices in standby mode). In this case, based on the Markov chain analysis, new electricity consumption profiles could be developed that would incorporate the aspects of consumer behaviour change. To avoid the discrepancies between the modelled and measured data, in detail analysis and development of specific household consumption profiles would be desirable. The development of such models should take into account the different circumstances in households – lifestyle factors, personal and socio-economic situation, the users personal beliefs and routine, the variety of households, as well as aspects of shared use of devices (for example, the whole family watching television together, or preparing the dinner for the whole family, but the equipment is operated – turned on, turned off and regulated by one person, etc.).

With the increasing diffusion of modern technologies (such as, wider deployment of smart meters), it will be increasingly important to develop different energy models based on user activities modelling. An important task would be to analyse the user profiles in different regions (urban areas, rural areas). Since in this thesis the Markov chain models were developed based on a typical summer (July) and autumn (October) months (as in the the „Consumption model"), and summer and winter months (as in the „Activity model" and „Appliance use model"), within the future research it would be beneficial to create new models, based on other month-profile modelling. In the further research it would be useful to carry out a detailed study for prediction of the long-term consumption reduction. Another important modelling task is to evaluate the change of transition probabilities if household adopts more rational use of energy, change the appliance use habits and uses more efficient electrical equipment. It is important to carry out a detailed analysis of how to improve the accuracy of the forecasting. As comprehensive Markov models characterize not only by the physical aspects of electricity consumption, but also the behavioural aspects, the new knowledge, understanding and expertise provided by this doctoral thesis is an invaluable addition to the research on this topic and will be useful in further research.

1.3. BENCHMARK APPLIACTION TO THE HOUSEHOLD SECTOR

In every household electricity consumption is different, therefore it is necessary to find a universal comparative indicator for comparison of the households. Household consumption profile is prominently stochastic, and consumption changes significantly over the day. It is quite difficult to develop a line-like benchmark, because in reality households' consumption is not constant over the day, but it depends on users' behavior. Consumption is higher in the morning and evening hours compared to the night hours and noon and midday. Thus benchmark application, allows reflecting real consumption profile, is more effective and useful in practice. Understanding of household electricity end use consumption allows developing corresponding energy efficiency strategies and programs in order to achieve the targets set in the household sector. To motivate users to implement more energy efficiency solutions in their homes, one way is to create a benchmark that is based on the results of analysis of the current situation. Benchmark application in this Thesis is applied for 4 daily profiles developed un smart metering pilot project data.

Considering EU legislative pressure with regard to smart metering system development as an effective tool for DSM integration in the households, it is expected that such systems can bring electricity consumption reduction. Benchmarks developed in the frameork of this Thesis are based on 2 alternatives:

- 1st alternative: electricity consumption reduction compared to the current situation is around 10%;
- 2nd alternative: electricity consumption reduction is 6%.

The results of the evaluation of both benchmark alternatives are shown in Figure 15.

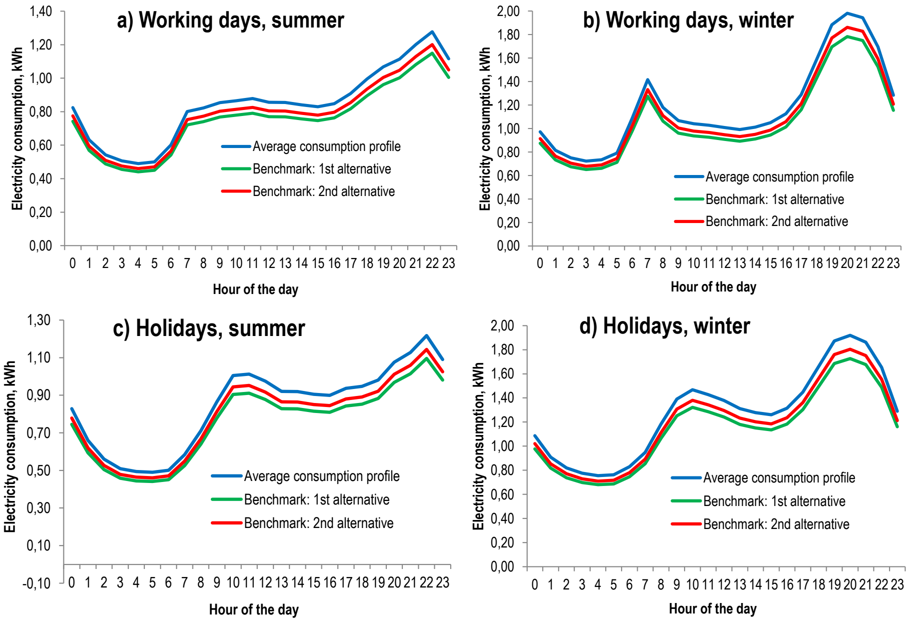

Fig. 15. Estimated household benchmarks for 4 types of the day

The assumptions put for each alternative based on literature review that indicates 5-15% electricity consumption reduction due to the integration of the smart metering system in households [29, 82-86, 88-93, 97-105] – i.e., assumption for the 1st alternative. However, the 2nd alternative foresees lower consumption reduction within the range of 1-10% [87, 94-96, 106-108]. As the results of scientific studies claim, 6% or 10% consumption reduction can be achieved through the change of users' behavior and ensuring rational energy use. The evaluation of the benchmarks shows (see Fig. 15) households should aspire for the consumption level that corresponds to the 1st benchmark alternative, since it brings 10% of consumption savings compared to the current situation. Such an alternative can be applied in the long-term in order to achieve consumption reduction within the household sector. The 2nd alternative reflects the potential short-term situation to reduce consumption.

2. EVALUATION ON CLIMATE CHANGE AND CO_2 EMISSION

Electricity consumption causes direct and indirect effects on climate change. To ensure sustainable energy consumption, it is necessary to reducē the influence on climate change. It is known that electricity production, distribution, transmission and consumption are connected with GHG emissions. Assessment of GHG emissions (or CO_2) in the household electricity consumption sector is connected with amount of electricity consumed in the households and amount of emissions from each consumed kWh. In this work, assessment of effects on climate and environmental sustainability due to the CO_2 emissions is based on comparison of the current situation and forecasts using data from the JSC „Latvenergo" pilotproject.

Electricity consumption for the baseline situation in the JSC „Latvenergo" pilotproject, against which the consumption savings in the pilotproject is compared, is derived based on pilotproject energy efficiency indicator – planned and obtainable CO_2 emission reduction of 10% or 267,975 t CO_2/year. Meanwhile CO_2 emission factor of 0,397 t CO_2/MWh defined in the Cabinet of Ministers of Latvija Regulations Nr. 608 and is used for assessment of pilotproject's resultative indicators. In order to evaluate emission changes in some time period (in the year period), it is important to ensure real-time electricity consumption monitoring that can be implemented with help of the smart meters.

Electricity consumption changes in the i-year against the baseline year is calculated according to the following equation:

$$E_b = \frac{CO_{2\_b}}{E_{CO_{2\_el}}}, \tag{15}$$

where:

CO_{2_b} – is baseline CO_2 emissions, t CO_2;

$E_{CO_{2\_el}}$ – CO_2 emission factor for electricity production, t CO_2/MWh.

Overall CO_2 emission from household electricity consumption in the i-year (CO_{2i}) is calculated using the following equation [87]:

$$CO_{2i} = E_i \cdot E_{CO_{2\_el}}. \tag{16}$$

In order to calculate CO_2 emission changes in the i-year, electricity consumption changes in the i-year compared to the baseline year are multiplied with an emission factor:

$$\Delta CO_{2i} = \Delta E_i \cdot E_{CO_{2\_el}}, \tag{17}$$

where:

ΔCO_{2i} – CO_2 emissions changes in the i-th year,t CO_2.

CO_2 emission calculation based on equations (15-17) and emission comparison can be done with 4 approaches, using different CO_2 emission factors, as shown in Table 5.

Table 5

CO_2 emission factors

CO_2 emission factors	CO_2 emission factor indication	CO_2 emission factor value, t CO2/MWh
Climate Change Financial Instrument (CCFI) average CO_2 emission factor for co-financed projects [145] – i.e., CCFI emission factor	$E_{CO_{2\_CCFI}}$	0,397
The Intergovernmental Panel on Climate Change (IPCC) defined standardized CO_2 emission factor for Latvia [146-148] – emission factor	$E_{CO_{2\_IPCC}}$	0,109
Life Cycle Assessment (LCA) defined CO_2 emission factor for Latvia [149-150] – LCA emission factor	$E_{CO_{2\_LCA}}$	0,563

At the moment, smart meter data from the 1st of April 2013 till 31th of March 2015 (2 years) are available. Therefore the first period for electricity consumption assessment in the households was set as the first year of pilotproject implementation from 1st of April 2013 till 31st of March 2014 – i.e, E_{2013}. Electricity consumption of 500 pilot project households for this period was 5341,93 MWh. The second period for electricity consumption assessment in the households was set as the second year of pilotproject implementation from 1st of April 2014 till 31st of March 2015 – i.e, E_{2014}. Electricity consumption of 500 pilot project households for this period was 5243,91 MWh. E_{2013} and E_{2014} will be compared with the baseline situation – electricity consumption for the 2012. Based on the equation (15) and the estimated CO_2 emission reduction for the baseline situation 2679,75 t CO_2/year and CO_2 emission factor 0,397 t CO_2/MWh, the estimated electricity consumption for the baseline situation is 6750 MWh.

CO_2 emission assessment results, where 2 evaluation periods are compared based on equations (15) – (18), as well as CO_2 emission assessment according to 3 emission factors (Table 5), are summarized in Table 6.

Table 6

CO_2 emission reduction results and comparison

Assessment period, year	Electricity consumption reduction against the baseline situation, MWh	CO_2 emission reduction using $E_{CO_2\_CCFI}$	CO_2 emission reduction using $E_{CO_2\_IPCC}$	CO_2 emission reduction using $E_{CO_2\_LCA}$
2013	1408,07	559	153	793
2014	1507,09	598	164	848
CO_2 emission reduction changes, %				
2013		-20,93%	-5,77%	-29,66%
2014		-22,38%	-6,19%	-31,71%

The results of CO_2 emissions assessment compared to the reference situation is graphically shown in Figure 16.

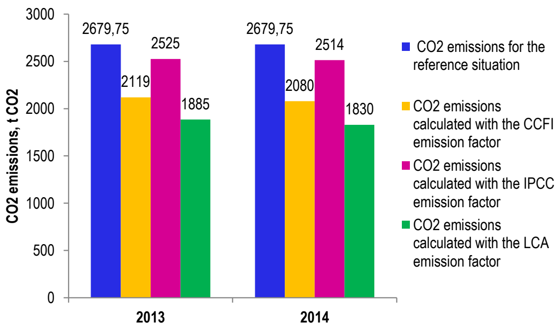

Fig. 16. The assessment results of the pilot project CO2 emission reduction using 3 CO2 emissions factors

As it can be seen, in the both aseessment periods electricity consumption and CO_2 emissions have decreased. Nevertheess, if we compare the results wit the baseline situation (year 2012), higher consumption reduction against the baseline situation (year 2012) was achieved in the second project year – 22,38%, than in the first project year – 20,93%. These results are calculated applying CCFI CO_2 emission factor for the Climate Change Financial Instrument co-financed projects. Higher CO_2 emission reduction can be obtained applying LCA emission factor, where CO_2 savings for the first year of the pilot project (2013) would be 29,66%, but for the second year of the pilot project implementation (2014) – 31,71%. Meanwhile, if IPCC emission factor was applied, CO_2 emission reduction compared to baseline situation would be lower – 5,77% in 2013 and 6,19% in 2014.

3. MODELING OF ENERGY EFFICIENCY MEASURES

One of main significant principles of sustainable electricity consumption is to ensure rational and optimal electricity use along with reasonable costs. This aspects is foundamental for the cost balance. Households with their electricity consumption habits influence not only their own costs, but also total costs of the electricity system. Modeling is based on information gathered during the second questionnaire of 30 households, where particular energy efficiency measures were specified. Electricity consumption reduction is modeled based on 2 measures: replacement of light bulbs to LED bulbs and switching off the appliances of stand-by regime consumption. Based on the questionnaire data, mean values were summarized and determined, which were used to define modeling assumptions. Modeling assumptions were based not only on the data from questionnaires, but also from literature review about efficient light systems and power reduction from switching off the stand-by regime of different devices. Based on summarized information and set assumptions, calculation of electrcity consumption reduction in particular periods of the day was performed. Consumption reduction potential was evaluated using average household consumption profile obtained form the pilotproject households that have smart meters, and a new profile was created based on modelling results. All the assumptions and detailed description of the energy efficiency modeling are not included in the Summary of doctoral thesis, buti can be found in the 4th capter of Doctoral Thesis.

Electricity consumption changes due to the replacement of existing light bulbs to LED bulbs are analyzed unded 3 scenarios developed, as shown in Table 7.

Table 7

Developed scenarios of efficient lighting

Scenario	Description
1st scenario: „Pessimistic scenario”	Considering that LED technologies are becoming even more popular also within the households, even in the case of a pessimistic scenario it can be assumed that at least 20% of the households will replace old lighting (incandescent bulbs) to new, energy efficient lighting (LED bulbs)
2nd scenario: „Optimal scenario”	It is assumed that 50% of the households are ready to implementē lighting sstem's replacement. This assumption is fairly realistic considering that 15 of 30 respondents mentioned that they would replace the current light bulbs to LED.
3rd scenario: „Effective scenario”	It is assumed that all the households, or 100%, will perform the lighting system's replacement.

The modeling results in case of 4 typical daily profiles and 3 scenarios due to the lighting system replacement of 20%, 50% and 100% are shown in Figure 18.

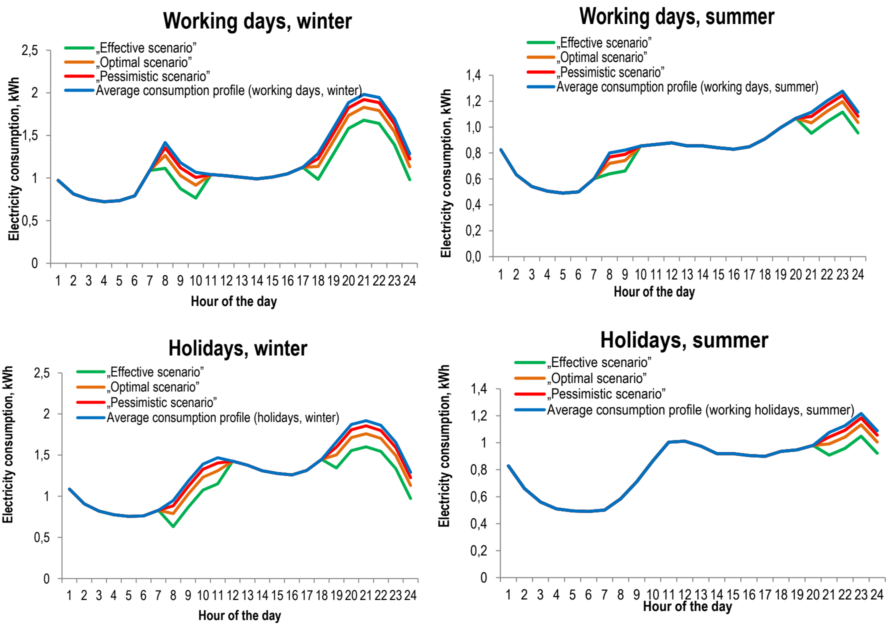

Fig. 18. Modeling results ofenergy efficient lighting installation for 4 daily profile

The modeling results (see Fig. 18) show the potential of the load shifting based on the lighting replacement at different times of day and different types of day and seasons. Based on the results of the study, if all households in Latvia would implement energy-efficient lighting, it would give the morning and evening „peak" consumption reduction of 21 to 22% during the winter and 15 to 16% in summer. Conversely, if only half of all households in Latvia will change the energy-efficient lighting, it wold lead to winter „peak" reduction by 10-11% and in summer 7-8%. Therefore, the installation of energy-efficient lighting provides a great potential for the morning and evening „peak" consumption reduction. Given the fact that the lighting in Latvian households account for only a small part of total consumption (around 15% during the winter and 10% in summer), the installation of energy-efficient lighting will not cause significant impact the overall average daily consumption reduction. If all households will implement the energy-efficient lighting, it will lead to 9% reduction of consumption during winter and 3% during the summer. If only half of the households will do it – the average consumption would be reduced by 4 – 5% in winter and by 1 – 2% in summe.

In all of the diagrams, a blue line indicates mean household electricity consumption profile in kWh for each hour for 4 day types (calculated on the basis of on consumption data of 315 target group households in the period from the 1st of April 2013 till 31st of March 2014). Scientific data show that the highest electricity savings can be obtained in case of effective scenario, when all of the incandescent light bulbs are replaced with the LED bulbs. The highest electricity consumption reduction among the modeled periods in the case of effective scenario is observed for the winter weekends (22%) that allows to reduce the average daily electricity consumption of 9% in this period.

Likewise, electricity consumption changes, when households stop using a stand-by regime, are analyzed in case of 3 scenarios as shown in Table 8.

Table 8

Scenarios for switching off electric devices in the stand-by regime

Scenario	Description
1st scenario: „Pessimistic scenario"	It is assumed, that not all inhabitants will switch off their devices in the stand-by regime as often as they indicated. It is due to their habits and inconveniences that switching off devices may cause. In the scenario, it is assumed that around 10% of the households will switch off their devices in the stand-by regime.
2nd scenario: „Optimal scenario"	It is assumed that 26,7% of the households are ready to switch off devices in the stand-by regime. This assumption is based on the survey where 8 of 30 respondents mentioned that they will be ready to do so.
3rd scenario: „Effective scenario"	It is assumed that all the households, or 100%, will switch off their devices in the stand-by regime.

Modeling results for electricity consumption reduction in case of switching off devices in a stand-by regime were modeled based on average consumption profiles for 4 day types and 3 modeling scenarios (10%, 26,7% and 100%). In this case only those households who have indicated information on the number of electrical devices which have stand-by regime (TV sets, computers, decoders etc.) were used for calculations. Based on target group household data, the average stand-by regime load was evaluated – 0,0262 kW. The modeling period is determined as time period from 9:00 – 17:00 (when people are at work) and 00:00-7:00 (when people are sleeping an not using the appliances). Mean consumption reduction for the modeling period and total daily consumption reduction from switching off a stand-by regime for the effective, optimal and pessimistic scenarios for 4 day types are shown in Table 9 and illustrated in Figure 19.

Table 9

Results consumption reduction from switching off the device in the staned-by regime

Scenarios	Mean consumption reduction in the modeled period				Total mean daily consumption reduction			
	WD, winter	WD, summer	WE, winter	WE, summer	WD, winter	WD, summer	WE, winter	WE, summer
Effective scenario	-2,83%	-3,79%	-2,50%	-3,68%	-1,77%	-2,37%	-1,56%	-2,30%
Optimal scenario	-0,76%	-1,01%	-0,67%	-0,98%	-0,47%	-0,63%	-0,42%	-0,61%
Pessimistic scenario	-0,28%	-0,38%	-0,25%	-0,37%	-0,18%	-0,24%	-0,16%	-0,23%

As can be seen from the research results, mean total consumption reduction from switching off the stand-by regime is insignificant – within the range of 1% – 2%. The highest savings for switching off devices in the stand-by regime can be obtained in the case of the effective scenario in summer – the average reduction for the modeling period 3,79 % for working days and 3,68 % for the weekend. That would let to achieve average total consumption reduction for working days and weekends 2,37 % and 2,30 %, correspondingly. The average reduction for the modeling period in winter time – around 1,67 %, that wold lead to the average consumption reduction of 0,54%. In the case of the pessimistic scenario, the total consumption reduction in summer is defined within the range of 0,23 % – 0,24 %, but in winter – 0,17 %.

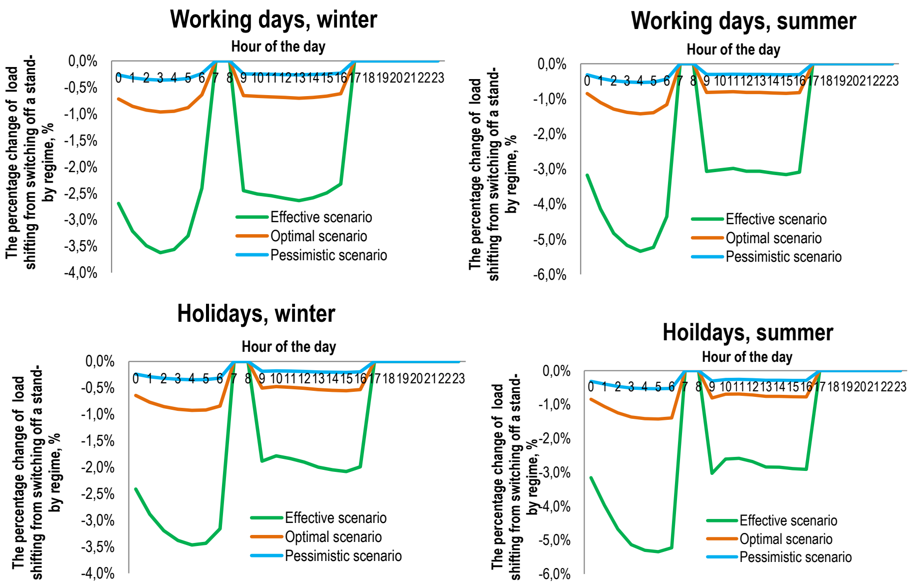

Fig. 19. The percentage change of the average consumption profile in case of stand-by consumption reduction for 4 day types and 3 modeling scenarios

Based on scientific data analysis, it can be concluded that if each household will switch off all the devices in the stand-by regime it can give 2% consumption reduction, in average.

CONCLUSIONS

1. The doctoral thesis presents the analysis of the factors influencing electricity consumption by application of multiple regression analysis. The results of quantitative data regression model showed that statistically the most important factors that affect the increase of electricity consumption are: the building area, the number of household inhabitants, income, respondent age, the existence of electrical heating systems, electric ovens with or without oven, electrical saunas, electrical water heating systems, air humidifiers, ventilation equipment and energy-saving bulbs, fryers, electric firewood chopping devices and other electrical equipment used outside of the house. Statistically significant negative effect on the changes in consumption were observed with tumble dryers, vacuum cleaners and other kitchen appliances. The correlation coefficient of the regression model indicates that the factors included in the model allow explaining 82,54% of the changes in electricity consumption.

2. The results of qualitative data regression model showed that statistically the most important factors that affect the increase of electricity consumption are: household type (i.e., private house) and if more household wants to receive comparative information about typical (mean) electricity consumption in the households with similar electricity consumption range. The factors as – if a respondent is female, if LED bulbs are mainly used in the household, if the respondents' are well aware on advantages of energy-efficient light bulbs and LED bulbs, people always switch off electrical appliances from standby mode, if wants to reduce the costs of consumed electricity, if wants to receive information about energy efficiency measures and if more households with insulated cellar, floor, doors, attic, sealed windows in the household – means – cause a negative impact on electricity consumption changes. The correlation coefficient of the regression model indicates that the factors included in the model allow explaining 40,87% of the changes in electricity consumption.

3. The determinants of electricity consumption savings were evaluated using the multipleregression analysis. Regression analysis showed that smart meters are statistically significant factor that positively affects the electricity consumption savings. Higher savings have been achieved in a target group, compared to the control group. Research results show that statistically the most important factors that positively influence the achieved savings are – group of participance, building area, coffee machines, laptop andf tablet computers, saunas, solariums, CRT televisions, electric gates, portable electgrical heaters, ground heat pumps, air heat pumps, the electrode boilerd and solar collectors. But statistically the most important factors that adversely affect the savings are – other kitchen appliances, the existence of electrical gates, air conditioning systems and the existence of the water source heating system, then savings are smaller. The overall correlation coefficient of the regression model indicate that statistically significant factors included in the model can explain 63,35% of the changes in electricity savings.

4. The doctoral thesis incorporates development of three probabilistic analysis models, that are based on Markov chain – the „Consumption model", „Activity model", „Appliance use model". The modelling results show that the Markov chain is sutable for „typical" electricity consumption profile representation with high precision. For the „Consumption model" the average difference between modelled and actual profiles in Markov chain model did not exceed 10%, but the difference in error between the states of consumption of positions is less than 3%. Markov chains can be used to predict with a moderate precision the monthly electricity consumption. Moreover

the Markov model allows to simulate the cyclical pattern of consumption. However, additional analysis showed that in order to achieve better accuracy, Markov chain models should be separately applied to the individual season and day type. Cross-validation test showed that the Markov chain models are able to reproduce electricity consumption for other households. The results of „Activity model" and the „Appliance use model" showed lower accuracy, where the difference between synthetic and real data were on an average of 30 %.

5. In the Thesis two benchmarking alternatives were presented on the basis of the monitoring system implementation in the household sector. The benchmarks were applied to four types of typical consumption profiles (calculated on the basis of smart meter pilot project monitoring data in 2013) showing consumption reduction potential. In order to encourage households to reduce consumption, the 1st benchmark alternative is preferable to attain the higher savings (i.e., 10%) compared to the existing situation. If the 1st alternative is achieved, it contributes to the decrease in consumption in the household sector in the long term.

6. The results of energy efficiency potential modelling showed that the installation of energy efficient lighting has the largest potential both to reduce „peak" load and the average electricity consumption of the day. The largest potential for reducing electricity consumption from replacement of old lighting is estimated during winter weekends, if the efficient scenario is implemented (100% replacement of lighting to LED light bulbs). In this case the „peak" consumption in the morning and evening hours could be reduced by 22% range, which makes it possible to achieve the average consumption decrease of 9%. Also optimal (50% lighting replacement) and the pessimistic (20% lighting replacement) showed the high potencial for „peak" consumption reduction in winter time, where average consumption reduction for these scenarios is estimated 5% and 2%, respectively.

5. The results of energy efficiency modelling for switching appliances from standby regime to off regime, showed that the average Latvian household has small potential for standby consumption reduction. Based on the data from pilotproject, the average standby power in the household is estimated to be 26,2 W. The largest reduction potential could be achieved through the efficient scenario (if all households would switch of stanby regime), where the average reduction in the modelling period during the summer period is 3,7 %, which results in overall reduction of the average consumption of 2,35 %. While during the winter the average daily reduction potential was evaluated 1,67 %. In the case of optimal scenario it is possible to reach average consumption reduction by 0,62 % during the summer and 0,45 % during the winter. But in case of the pessimistic scenario (where practically nothing woul be done) the overall decrease in average consumption during the summer period is estimated at 0,24% level, while in the winter – 0,17 %. Based on scientific data analysis it can be concluded, if every household would switch off appliances from standby regime, the average decrease of consumption would be 2 %.

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Ilze Laicane

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Summary of doctoral thesis

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