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Research and Development of Storage Based Energy Management System for Households

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

Denis Lebedev................................

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ENERGEETIKA. ELEKTROTEHNIKA. MÄENDUS D82

Energiasalvestil põhineva energiahaldussüsteemi uurimine ja väljatöötamine kodumajapidamistele

DENIS LEBEDEV

TTÜ KIRJASTUS

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Denis Lebedev

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LIST OF PUBLICATIONS

[I] Lebedev, D.; Rosin, A.; Auväärt, A. (2012). Profitability of Energy Storages for Household Load Scheduling. In: 11th International Symposium "Topical Problems in the Field of Electrical and Power Engineering". Doctoral School of Energy and Geotechnology. II : Pärnu, Estonia, January 16-21, 2012, Ed. Zakis, J. Elektriajam, 70−75.

[II] Melentjev, S.; Lebedev, D. (2013). Overview of Simplified Mathematical Models of Batteries. In: J. Zakis (Ed.). 13th International Symposium "Topical problems in the field of electrical and power engineering". Doctoral School of Energy and Geotechnology. II : in memoriam of professor Juhan Laugis : Pärnu, Estonia, January 14-19, 2013 (231−235). Pärnu: Elektriajam.

[III] Rosin, A.; Auväärt, A.; Lebedev, D. (2012). Analysis of operation times and electrical storage dimensioning for energy consumption shifting and balancing in residential areas. Electronics and Electrical Engineering, 4 (120), 15 – 20.

[IV] Rosin, A.; Auväärt, A.; Lebedev, D. (2012). Energy storage dimensioning and feasibility analysis for household consumption scheduling based on fluctuations of Nord Pool Spot price. Przeglad Elektrotechniczny, 88(1a), 37 - 40.

[V] Lebedev, D.; Rosin, A. (2014). Modelling of Electricity Spot Price and Load Forecast Based New Energy Management System for Households. 55th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga Technical University, Riga, October 14, 2014. Latvia: IEEE, 222−226.

[VI] Lebedev, D.; Rosin, A. (2015). Practical Use of the Energy Management System with Day-Ahead Electricity Prices. 2015 IEEE 5th International Conference on Power Engineering, Energy and Electrical Drives (POWERENG), Riga, Latvia, May 11-13. IEEE.

[VII] Lebedev, D.; Rosin, A.; Kütt, L. (2016). Simulation of Real Time Electricity Price Based Energy Management System, IEEE IECON 2016, The 42nd Annual Conference of IEEE Industrial Electronics Society, October 24-27, 2016.

[VIII] Auväärt, A.; Rosin, A.; Belonogova, N.; Lebedev, D. (2011). Nord Pool Spot price pattern analysis for households energy management. *In: 7th International Conference-Workshop Compatibility and Power Electronics (CPE2011), Tallinn, Estonia, June 01-03, 2011:* IEEE, 2011, 103 - 106.

[IX] Auväärt, A.; Rosin, A.; Müür, M.; Lebedev, D. (2011). Nord Pool Spot price fluctuation analysis for energy management of household appliances. 10th International Symposium "Topical Problems in the Field of Electrical and Power Engineering", Doctoral School of Energy and Geotechnology. Pärnu, Estonia, January 10-15. Ed. R. Lahtmets. Tallinn, Estonia: Estonian Society of Moritz Hermann Jacobi, 91−94.

In Appendix 2, copies of publications with classification 1.1 and 3.1 are included.

Author’s Contribution to the Publications

Author’s contribution to the papers included in the thesis is as follows:

[I] Denis Lebedev is the main author of the paper, responsible for the literature review, data collection and calculations. He had a major role in writing and presented the paper at 11th International Symposium "Topical Problems in the Field of Electrical and Power Engineering". Doctoral School of Energy and Geotechnology. II. 2012.

[II] Denis Lebedev co-authored the paper, responsible for the literature review, data collection, and some of the calculations. He had a minor role in writing.

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ABBREVIATIONS

A	Ampere
Ah	Ampere-hour
AC	Alternating current
AGM	Absorbent glass mat
ASCII	American Standard Code for Information Interchange
DB	Data block
BCDS	Battery charge discharge schedule
BESS	Battery energy storage system
BM	Battery Monitor
CAES	Compressed air energy storage
CET	Central European Time
CPU	Central processing unit
DAA	Day-Ahead algorithm
DC	Direct current
DCE	Data circuit-terminating equipment
DMC	Digital Multi Control
DoD	Depth of discharge
DR	Demand response
DSO	Distribution system operators
DTE	Data terminal equipment
ECMA	European Computer Manufacturers Association
EE	Energy Efficiency
EMS	Energy Management System
ES	Electricity storage
EV	Electric Vehicle
GUI	Graphical user interface
GWh	Gigawatt-hour
HD	Holidays
HEMS	Home Energy Management Scheduler
HMI	Human Machine Interface
HVAC	Heating, Ventilation, Air Conditioning
ISO	Independent system operator
I/O	Inputs/Outputs
kW	Kilowatt
kWh	Kilowatt-hour

LA	Lead acid
LAD	Ladder Logic
MW	Megawatt
MWh	Megawatt-hour
NP	Nord Pool
PC	Personal Computer
PHES	Pumped hydroelectric energy storage
PLC	Programmable Logic Controller
PROFINET	Process Field Net
PU	Power Unit
PV	Photovoltaic
RTC	Real-Time control
RTO	Regional transmission organization
RTM	Real-Time monitoring
RTP	Real-Time price
RTPA	Real-Time price algorithm
SCADA	Supervisory Control and Data Acquisition
SCL	Structured Control Language
SFE	Supply function equilibrium
SQL	Structured Query Language
SR	Spinning Reserves
SMA	Simple moving average
SMES	Superconducting magnetic energy storage
SOC	State of charge
STC	Stochastic scheduling control
TCP/IP	Transmission Control Protocol and the Internet Protocol
TIA	Totally Integrated Automation
TOU	Time of Use
TSO	Transmission system operator
TW	Terawatt
TWh	Terawatt-hour
UML	Unified Modeling Language
VB	Visual Basic
WD	Weekdays

SYMBOLS

C_{alg}	day average cost with use of an algorithm
C_{DAA}	day total cost with use of DAA
C_{RTPA}	total cost of energy for particular time period T with use of RTPA
C_{tot}	daily sum cost without the use of EMS
$DayP$	day profit achieved by EMS
$DayP_r$	required day profit to return investment to EMS
Δt	time step
$E_{bal,t}$	energy balance at hour t
E_c	electricity consumption
$E_{c,t}$	electricity consumption at the hour t
$E_{dir,c}$	direct consumption of electricity generated by a generation system
E_{DoD}	energy capacity equals to battery Depth of Discharge amount
$E_{g,t}$	electricity generated (or grid electricity) at the hour t
E_I	initial required energy capacity of battery bank
E_{Imax}	required maximum energy capacity for battery bank
E_{los}	total losses of electricity
E_{pp}	electricity generated by a generation system
$E_{res,c}$	indirect consumption of electricity generated by a generation system
E_{res}	daily demand for stored energy
E_{sp}	surplus of generated electricity
EMS_{total}	total cost of EMS
Fp	forecasted electricity price
Fr	required electricity price difference
H_{max}	margin for decrease of maximum level price
H_{min}	margin for decrease of minimum level price
i	actual battery current
i_C	charging current from the grid
it	actual battery charge
k_{res}	relative daily demand for stored electricity compared to the total demand
L_{max}	maximum level price
L_{min}	minimum level price
m	auxiliary variable for indexing
n	auxiliary variable for indexing
o	auxiliary variable
η_s	round-trip efficiency of energy storage
η_c	charging efficiency of energy storage
η_d	discharging efficiency of energy storage
P_C	charging power
P_D	discharging power
P_{grid}	power from the grid

P_{load}	load consumption
P_s	power output of energy storage
Pr	maximum profit generated by algorithm
Q	battery capacity
R	battery internal resistance
R_P	polarization resistance
$SOC(t)$	state of charge at the end of time slot t
t	index for time
T	time period consists of t slots
V	actual battery voltage
V_0	battery constant voltage
V'	exponential voltage
$x1$	decision variable (1 – for charging)
$x2$	decision variable (1 – for discharging)
z	coefficient shows required difference between minimum and maximum prices

INTRODUCTION

Motivation

The last year's period has seen a process of fundamental change in electricity supply industries. The deregulation of numerous power markets around the world, mainly the US and EU, has created liberalized markets with an optional or mandatory spot market [1]. As a result of that change, the Power Exchanges appeared as a consolidated entity where the supply and demand meet [2]. Assistance of the trading short-term standardized products is the significant goal of exchange-based spot markets. They provide other advantages, like a neutral price reference and a neutral marketplace, clearing and settlement service, safe counterpart and easy admission [3]. The latter allows for relatively small members participating in the energy market. Sharing by these members of renewable energy sources and hybrid systems, such as electric energy storage with wind turbines and photovoltaic panels, has increased electricity production remarkably and has influenced price formation in the power markets. In the open-market economic conditions and policies, efforts to find realistic models to define prices of electricity are essential for the evaluation of power grids [4]. In contrast to commodities, electricity moves permanently between market participants. As a result, a fair balance must be maintained between generation and consumption every hour – 365 days per year [5]. This is one of the differences from financial markets, though it is an opportunity for end customers to be involved in the trading process all the time. However, energy spot markets could have different features and time frame options. One of the largest in Europe, Nord Pool (NP), initially in 1993, covered only Norwegian market operations. During the next six years, it combined all Scandinavian countries to one pool [2]. Today, already 80 companies from 20 countries and regions, like Nordic and Baltic, trade on the two time frame markets. Total power amounts to almost 500 TWh in the day-ahead market and 5 TWh in the intraday market [6]. These are two main time frames in two specific markets. The first is the Elspot day-ahead market with physical delivery. The products traded are power contracts on a daily basis with one hour duration and block bids. The hourly contracts cover hour by hour all 24 hours of the following day. The intraday market is Elbas, which mostly supplements day-ahead market and secures the essential balance between physical contracts of the participants in the power market. The trading products are one hour physical delivery contracts, trading of which takes place around the clock to one hour before distribution [3]. It should be noted that most of the power volume handled by NP is transacted on the day-ahead market, but the benefit of intraday market in power regulation is obvious.

From April 1st, 2010, the Estonian electricity market joined the NP bidding area with the help of Estonian national grid company Elering. It should be mentioned here that the constraint in the electricity market participation was an annual draw of electricity in 2 GWh. Nevertheless, since January 1st, 2013, all participants in Estonia became eligible consumers in the fully open electricity market [7]. It would be unfair not to mention this motivation fact, which has opened possibilities of demand side management for small consumers and their households in Estonia. The idea consists in the assets planning needed to meet the demand of the following day or hour, and encourage the end user to acquire less grid energy during peak price hours and move the time of energy use to off-peak times [8].

Thesis objectives and tasks

The main objective of the thesis is to study the possibility to use electrical energy storage for balancing of energy consumption in households and development of a new energy management system. Another aim is to develop algorithms for energy management in day-ahead and intraday electricity market conditions with the help of electrical energy storage.

This research is important because many theoretical approaches are encountered in electrical energy storage control, but still practical implementations of these systems are scarce, especially those for small customers who live in apartments, i.e. those for households. The public in general tends to believe that customers are well aware of the electricity market in Estonia since it has been fully open for several years; however, price stochastic fluctuations and their influence on small consumers has been scarcely studied. On the other hand, reduction of energy storage costs and small-scale renewable sources bring new participants to the Estonian electricity market. Thus, the task of the thesis regarding to the theoretical part is to determine the benefits of energy storage with open electricity market prices also for smaller customers. Furthermore, installation of the small-scale energy management system, like the practical part of the thesis task, is essential to confirm the theoretical part in the limits of Estonian energy market activity. Therefore, studies in that area are required.

Research tasks

The task is to create a Research and Development of Storage Based Energy Management System (EMS) for households, which includes:

1. Overview of open electricity market and demand side management technologies, research of energy storages suitable for household systems
2. Development and evaluation of control models for electrical energy storage based on the electricity market price with different time resolution
3. Design and development of a new Energy Management System, with a description of sub- systems
4. Research of economical evaluation of the Energy Management System, verification of the system by practical measurements.

Contribution of the thesis and novelty

The scientific contributions of the thesis can be summarized as the research and development of a new energy management system for typical households with the use of a battery energy storage system as follows:

- review of NP electricity markets and energy storage technologies;
- analysis of load patterns and time dependence of electricity consumption in typical households;
- research and development of day-ahead price based control model/algorithm (price trading time frame 24 hour) for a new storage based EMS;
- research and development of real-time price based control model/algorithm (price trading time frame 1 hour) for a new storage based EMS;
- development of architecture of a new storage based EMS;
- development of supervision models/algorithms for a new storage based EMS;

and the practical result, as a part of dissemination, which includes:

- new energy storage integrated energy management system;
- new software for control of the energy management system (including server PC with data management and fetching data from energy operator);
- economical evaluation and verification of EMS
- control guidelines for the new energy management system with an overview of prospective development possibilities.

Thesis outline

The thesis is divided into four chapters, the Introduction and Conclusions.

- Chapter 1 provides an overview of the open electricity NP market and energy storage technologies for demand side management.
- Chapter 2 studies mathematical models for energy shifting with a battery energy storage system (BESS), development of day-ahead price and real-time price based control algorithm.
- Chapter 3 describes the research and development of the new Energy Management System.
- Chapter 4 presents economical evaluation of the new Energy Management System.

1. STATE OF THE ART AND RECENT ADVANCES OF DEMAND SIDE MANAGEMENT

1.1 Open electricity market

Governments have considered the electricity production as a primary industrial segment throughout times. It is required to control electricity industry effectively because of its strategic meaning for industrial growth. Furthermore, electricity industry usually had monopoly characteristics and tended to impact environmental and social factors. Despite private ownership of the electric utilities in some countries, they still had wide-ranging financial and safety planning, and environmental control by the governments because of the lack of competition in the potentially competitive generation and supply business [9]. This situation started to change in the early 1980s when the process of deregulation of electricity market was developing in South America and spread to other world. Since the 1990s, the pace of electricity market deregulation and liberalization became faster. The most common arguments in support were: unbundling of the competitive functions of electricity industry from the monopoly functions and to establish a free wholesale and retail electricity market [10]. On the other hand, a number of key issues arose from the demonopolization of the electricity sector and open energy markets. For instance, independent bulk system grid operators in Real-Time coordinating the supply and demand of electricity can affect the quality of electricity transmission, since any failure on their grid can propagate to a very huge amount of end customers. These operators are termed transmission system operators (TSOs) in Europe; regional transmission organizations (RTOs) or independent system operators (ISOs) in the United States, and load dispatch centers in India. Doubtless, operators have all required certifications and resources to provide real-time dispatching of generation and managing security in power systems. Also, interconnection to each other on regional or national level reduces the possibility of any concern; however, natural hazards and generation - consumption unevenness cannot be avoided completely [11]. Another major factor of open electricity market is a trading model. There are three essential models in use for electricity markets today: the Cournot model, the Bertrand model, and the supply function equilibrium (SFE) model [12], which is well applied to the market structure of many restructured electricity markets, such as New Zealand, Australia, Pennsylvania-New Jersey-Maryland Interconnection, California Power Exchange, and NP. The bid format with the market-clearing price is precisely a supply function in these markets [10].

Since 2010, Estonian electricity market provides link to the Nordic electricity market – NP. In 2013, the market became fully open and from that moment, all consumers are eligible to purchase electricity through a broker or directly in the Estonia price area of NP. The result of electricity purchasing was its physical delivery to end customer with the help of TSOs and distribution system operators (DSOs). Thus, transmission and distribution that ensure electricity flow within the region on a par with production capacity are one of the main factors that influences the price of electricity in the open market. Estonia ensures connection capacity by physical interconnection to neighbor's power networks. The main power lines that connect Estonia with Nordic region are sea cables EstLink 1 and EstLink 2 with respective capacities of 350 MW and 650 MW [10]. Such a great electricity liquidity option leads to depth in the market and reliable index price, but also needs an extra balancing feature. For Estonia, the same as for other NP members, the intraday Elbas market is performing a role of balancing power for day-ahead Elspot market.

The Elspot and Elbas markets supplement each other in the balancing of supply and demand. Elspot can be termed as auction of power for delivery the following day (next 24 hours), where the price is determined for every hour [3]. Elspot processes the price on the basis of supply (sell), demand (buy) and transmission capacity (turnover). The bids are gathered together and the market-clearing price (system price) is calculated at their intersection of aggregated supply and demand curves [1] [13]. Figure 1.1 illustrates an example of processing the market-clearing price [6].

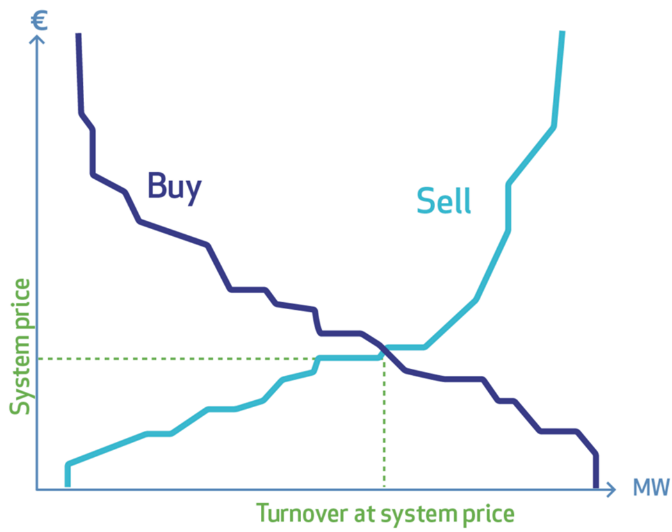

Figure 1.1 System price determination at NP [13]

An outline of the features regarding Elspot is as follows:

- operated contracts are physical-delivery electricity contracts for the following day;
- according to the type of the bid, contract duration is one hour or one block; blocks are scoped as several consecutive hours with one price;
- minimum size of the contracts is 0.1 MWh/h;
- 12:00 by Central European Time (CET) is the deadline hour for receiving all the bids for the following day;

- price calculation results appear for consumers from 12:45, latest at 14:00 by CET [14].

The last feature is essential for systems in the NP region, which uses day-ahead energy management models and algorithms.

Elbas market has less electricity turnover between supply and demand, as distinguished from Elspot, which takes the largest part of energy volume transmissions. However, as was mentioned above, Elbas is an intraday market, which is very important in terms of stable and balanced electricity market. Typical participants in this market are brokers, power producers, suppliers and distributors. The key features regarding Elbas intraday market are:

- operated contract is one hour before the delivery hour;
- new contracts are available when the Elspot prices for the following day have been set at 14:00;
- minimum size of the contracts is 0.1 MWh/h;
- minimum bid price is 0.1 EUR (€);
- Elbas market trading is available also in the Baltic region [6].

The latter is important for systems in the NP region, which use real-time price (RTP), with the time unit at least one hour, in energy management models and algorithms.

1.2 Demand side management possibilities in households

Traditionally, demand has been considered to be fixed and therefore it was considered to be preset. Nevertheless, with recent changes in the electricity grids and systems, more intermittent energy renewable production being applied, there can be a need of variable demand and it can no longer be treated as fixed and predetermined [15]. Demand Side Management (DSM) is a set of intersected and flexible programs which allow consumers a major role in adjusting and shifting their own demand for electricity during peak periods, and reducing their energy consumption overall [8]. Depending on the timing and the impact of the applied measures on the customer process, DSM can be divided into the following two categories:

- Energy Efficiency (EE), consuming less power to complete the same tasks. The efficiency includes a decrease of the demand by using more efficient high load appliances such as water boilers, fridges, or washing machines [16];
- Demand Response (DR), modifications in electric usage by end-use customers from their normal consumption patterns in reaction to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at the time of high wholesale market prices [17].

These categories include different approaches and programs. In [18], DSM is classified into categories shown in Figure 1.2.

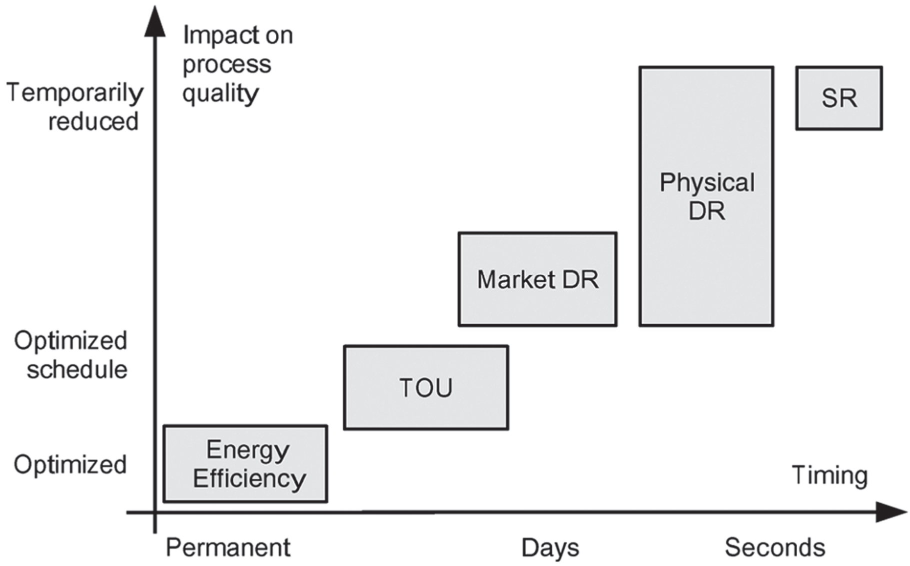

Figure 1.2 Types of DSM by [18]

In the figure, TOU is Time of Use program. The consumers react to the presented different prices for electricity at different times by shifting demand from high to low cost price periods. An option of this encouraging mechanism is Dynamic TOU pricing where consumers can adjust their use of electricity with reasonably short announcement times, i.e. 24 hours in response to notified price changes [19]. Market DR means consumer's changes in electric usage by means of Real-Time pricing (RTP) and other incentives price signals; physical DR stands for more global approaches like a grid for more efficient management and emergency signals from TSOs [18]. The Spinning Reserves (SR) implemented by loads represent the upper end of the DSM time frame spectrum and are considered as primary (active power output directly depends on the frequency) and secondary control (restoring frequency and grid state with additional active power) [20]. According to [17], TOU is a program of DR in the Non-Dispatchable response category. This category is also termed as Non-Event Base because it cannot be considered as verifiable during system peak loading periods. Dispatchable or Event-Base programs are consistent and capable of reacting within Independent System Operator (ISO) or Regional Transmission Organization (RTO) time guidelines [17]. This thesis specifies TOU and RTP as a part of DR based on the market pricing.

1.3 Energy storage technologies for demand side management

The improvement of the DR approach is the use of energy storage (ES) in DSM on the consumer side. The simplest definition of a storage device is specifically designed to store electricity from the grid, convert it into an energy form suitable for storage, subsequently convert it back into electricity and return it to the grid [I]. An example is the use of ES units to store energy during off-peak hours and discharge them during peak hours. ES is essential to balance supply and demand. Peaks in demand can frequently be anticipated and fulfilled by increasing or decreasing generation at fairly short notice. Higher levels of energy storage are required for grid flexibility and grid stability and to cope with the increasing use of intermittent wind and solar electricity [21]. In addition, the main energy storage functionalities such as energy time-shift and energy extraction are expected to make a large contribution to security of power supplies, power quality and minimization of direct costs and environmental costs. On the other hand, to ensure influence on the improvement and emergence of the Smart Grid concept at all voltage levels, ES has to be integrated in network-based energy systems, in the electrical grid system, heat and cooling network and gas networks [21].

Another way of looking at ES use in DSM is the problem of ES optimal dimension. It is an important area in the development of micro- and Smart GRID technologies to increase system reliability and to reduce the profitability time. Properly chosen ES technologies will smooth out online balancing of supply and demand and allow electricity to be dispatched later [22]. In this thesis, a DSM system is considered as a small-scale energy system for an end-user household system.

Depending on the location of storage, the systems can be divided into large-scale (scaled in gigawatts GWs), medium-sized (scaled in megawatts MWs) or micro, local systems (scaled in kilowatts kWs) [21]:

- Large bulk energy (GW):
    - Thermal storage, pumped hydro;
    - Compressed Air Energy Storage (CAES);
    - Chemical storage;
- Grid storage systems (MW) able to provide:
    - Superconducting Magnetic Energy Storage (SMES);
    - NaS & Flow batteries;
    - Pumped Heat Energy Storage (PHES);
- End-user storage systems (kW):
    - Power: supercapacitors, flywheels;

o Energy: batteries - Lead acid and Li-ion [21].

Pumped hydro, thermal storage, chemical storage (hydrogen) and CAES are large bulk energy providers; thus they do not suit well for small-scale energy systems. They have large size and high costs and therefore have a wider use in utility scale installations. SMES is high-power equipment that has MW scale range. It is a high efficient device that can withstand several cycles without significant loss of energy storage capacity, but it has high execution expenses and the technology is in the stage of improvement [23] [24] [25]. Flow battery characteristics include high power and low self-discharge as compared to other forms of storage technologies; however, it is not yet suitable for integration at households [26] [27]. PHES is also hard to implement at small-scale households.

Small storage systems of high power devices are represented by kinetic ES, mostly based on flywheel technology and supercapacitors. These ESs are used mainly for short duration, high-power discharges and are therefore widely used in the uninterruptable power source market [10]. Nevertheless, flywheels and supercapacitors are short-time duration energy storages, and not suitable for energy management in households.

Today, by the scope of parameters and properties, batteries as ES are still the best solution for DSM in a small-scale customer system. The battery storage device is described in [I] by:

- energy capacity - the amount of electrical energy the device can store, usually measured in kilowatt-hour (kWh), megawatt-hour (MWh) or gigawatt-hour (GWh);
- power capacity - the maximum instantaneous output that an energy storage device can provide, usually measured in kW, MW or GW;
- efficiency - indicates the quantity of electricity which can be recovered as a percentage of the electricity used to charge the device;
- round-trip efficiency - indicates the quantity of electricity that can be recovered as a percentage of the electricity used to charge and discharge the device charging power capacity, and discharging power capacity;
- response time - the length of time it takes the storage device to start releasing power.

The relationship between state of charge (SOC) of the energy storage and the power flow in/out of the storage P_s is as follows [28]:

$$SOC(t+1) = \begin{cases} SOC(t) - \frac{1}{\eta_d} P_s(t)\Delta t \\ SOC(t) - \eta_c P_s(t)\Delta t \end{cases}, \tag{1.1}$$

$$\begin{gathered} P_s^{\min} \leq P_s(t) \leq P_s^{\max} \\ SOC_{\min} \leq SOC(t) \leq SOC_{\max} \end{gathered}, \tag{1.2}$$

where η_c and η_d - efficiencies of charging and discharging, respectively; t - index for time; SOC - state of charge of energy storage; Δt - time step; P_s - power output of energy storage. The round-trip efficiency of electricity storage is $\eta_s = \eta_c \cdot \eta_d$ [10].

One should, nevertheless, consider the problem from another angle. Battery use as ES, has the following shortcomings: permanent self-discharging, relatively low energy density and high dependence on environmental temperature. These are common technical flaws. To avoid any critical mistakes in planning and developing ES on the customer's side, the simulation of battery behavior should be done in accordance with the electrical model of battery. Specially developed electric-circuit based models can be used for accurate prediction of charge and discharge of batteries, taking the state of charge into account [II]. The general calculation (1.3) for the used battery model can be found in [29]:

$$V = V_0 - R_P \frac{Q}{Q - it} it - R_P \frac{Q}{Q - it} i - Ri + V', \tag{1.3}$$

where V – actual battery voltage (V), V_0 – battery constant voltage (V), R_P – polarization resistance (polarization resistance is the transition resistance between the electrodes and the electrolyte. An increased resistance to the flow of current in a voltaic cell is caused by chemical reactions at the electrodes. Polarization reduces the electric potential across the voltaic cell) [30] (Ω): Q – battery capacity (Ah); it – actual battery charge (Ah); R – battery internal resistance (Ω); i – actual battery current (A); V' – exponential voltage (V) [II].

The other side of the coin is economic considerations, such as price and lead-times for mass production, life expectancy and maintenance requirements. This makes the task of choosing the right battery type of utmost performance, as even the slightest differences in parameters may cause changes in the long-term use of ES in DSM control. However, the choice for the latter part can be considerably cut down by choosing from the most precise battery types for households (small-scale) [II], with a simplified consideration of technical parameters, and with the main criteria of battery energy storage system (BESS) - to match the demand for stored energy to cover household electricity consumption and bring economic benefit in the household use. This feasibility for households can be estimated by the system cost and profit calculation [I].

1.4 Demand for stored energy to cover household electricity consumption

BESS plays a major role in shifting critical (not shiftable) loads in household consumption patterns. It comes from open electricity market (NP in Estonian region) price fluctuations as a possibility of cutting electricity costs at households. Consumption of electricity at households in Estonia is around 35% of the whole national energy consumption, and in these terms it is one of the highest in the European Union [31]. Optimization of BESS capacitance and control models (including the charging/discharging cycles) is an essential research task. The key objectives of the customers are:

- to minimize costs of energy [10];
- to upgrade the power quality (maintains nominal voltage levels with nominal frequency levels) and comfort (provides back-up power for home appliances in the case of interruption with a grid) [32].

It should be noted here that comfort in household energy management is a major factor that affects the choice of BESS. According to consumer behavior, consumption priorities (load) can be divided into three main load groups: non-shiftable, almost shiftable, and shiftable. To find appurtenance of house appliances to load groups, an analysis [33] was done with four-week measurements (02.2012 – 03.2012) in an average Estonian household as a research object. The result of measurements found confirmation in the European Union research [34]. Figure 1.3 shows the total energy consumption by load in that apartment.

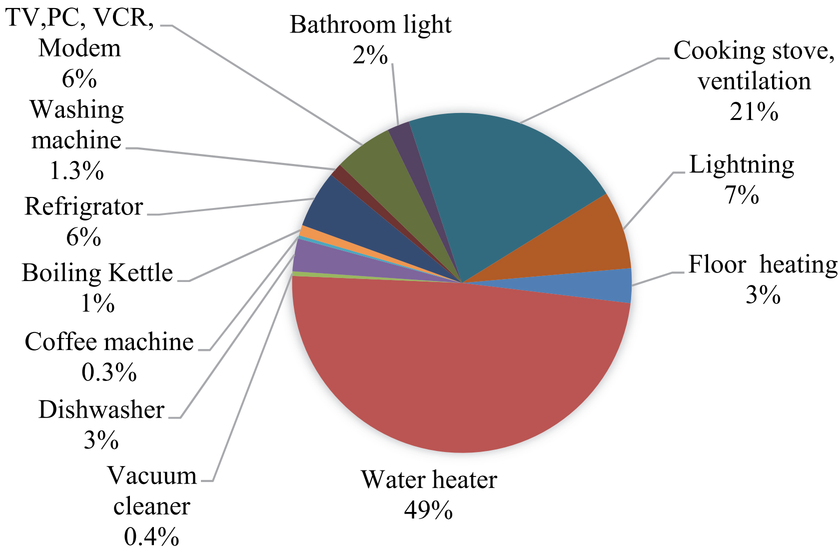

Figure 1.3 Load distribution of household appliances [33]

The part of non-shiftable load consumption constitutes approximately 36% of the total energy consumption by all appliances [33]. Despite the fact that the other larger part of energy consumption can be shifted with different methods of DSM, the customer comfort level is considered as a main goal in this research work. Therefore, in the scope of this thesis, the entire energy consumption of a household is considered as non-shiftable and BESS has to be dimensioned accordingly.

To find the precise amount of energy demanded in BESS, the energy balance of an electricity system should be taken with the following simplified formula [III]:

$$E_{pp} = E_c + E_{sp} + E_{los} \Rightarrow E_{pp} = \underbrace{E_{dir,c} + E_{res,c}}_{E_c} + E_{sp} + E_{los}, \tag{1.4}$$

where E_{pp} – electricity generated by a generation system; E_c – electricity consumption; E_{sp} – surplus of generated electricity; E_{los} – total losses; $E_{dir,c}$ – direct consumption of electricity generated by a generation system; $E_{res,c}$ – indirect consumption of electricity generated by a generation system (stored energy reserve of generated energy) [III].With the system losses equal to zero (E_{los} = 0) and analysis for workday and weekend separate periods (since they have different consumption patterns), energy balance $E_{bal,t}$ at the hour t can be calculated using (1.5):

$$E_{bal,t} = E_{c,t} - E_{g,t}, \tag{1.5}$$

where $E_{g,t}$ – electricity generated (or grid electricity) at the hour t; $E_{c,t}$ – electricity consumption at the hour t [III]. The demand for stored energy (1.6) to cover household power consumption from ES in a weekday (WD) or holiday (HD):

$$E_{g,t} \le E_{c,t} \Rightarrow E_{res} = \sum_{t=1}^{n} (E_{c,t} - E_{g,t}) = \sum_{t=1}^{n} \left| E_{g,t} - E_{c,t} \right|, \tag{1.6}$$

where E_{res} – daily demand for stored energy; $E_{res,t}$ – demand for stored energy at the hour t; n – 24 hours a day [10]. Furthermore, to describe the relative daily demand for stored electricity compared to the total demand (i.e. consumption), the coefficient k_{res} (1.7) can be used:

$$k_{res} = \frac{E_{res}}{E_c} = \frac{\sum\limits_{E_{g,t} < E_{c,t}} (E_{c,t} - E_{g,t})}{\sum E_{c,t}}, \tag{1.7}$$

where k_{res} – relative daily demand for stored electricity compared to the total demand (i.e. consumption). On the basis of these calculations and analysis [33] [III] [IV], the minimum energy reserves that an electrical energy storage system should have in most cases is 5 to 10 kWh, depending on functionality and consumption patterns. BESS with such parameters can be used in most energy consumption balancing and shifting cases. The peak power of the storage system should be approximately between 1.2 and 1.5 kW accordingly [IV]. Figure 1.4 illustrates the average daily electricity consumption is 1 kWh per hour [10]. Consumption curve lays on the tops and the bottoms of the chart columns. For the better overview of over- and under-consumption periods, start value of the horizontal axis crosses vertical axis at 0.9 kWh/h.

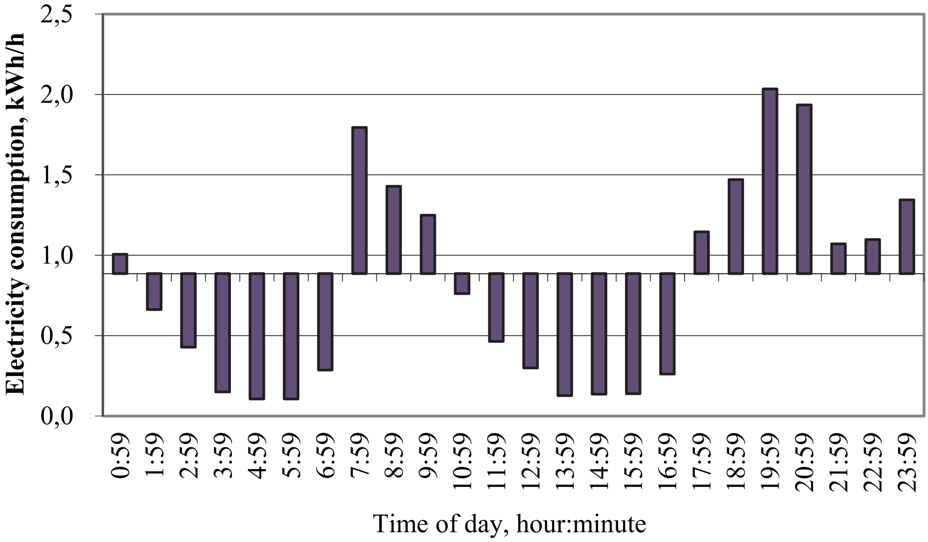

Figure 1.4 Average workday electricity consumption [10]

The consumption pattern of the hybrid ES system with BESS with DR prices for an average apartment shows the required maximum limit of energy storage capacity in the mean at 7 kWh [33] The European Union research co-funded by the Intelligent Energy Europe Program shows a similar result for Baltic countries at 6.8 kWh [34]. On the other hand, this amount of energy can be released only with 100% storage discharge. In real conditions, the depth of discharge (DoD) of ES should be less than 100% and both system life cycles and the required energy capacity limit will be increased. The new maximum life cycle number of different BESS can be found in Figure 1.5.

It is clear from these observations that at constant DoD value, the required energy capacity may be different from an initial energy capacity. The simple equation (1.8) establishes the final required energy capacity for shifting consumption with a particular DoD:

$$E_{l\max} = \frac{E_I}{DoD}, \tag{1.8}$$

where E_{lmax} – required maximum energy capacity and E_I - initial required energy capacity [I].

Thus, lead acid (LA) BESS to provide 1000 cycles has to be dimensioned roughly three times higher (1.9):

$$E_{l\max} = \frac{7kWh}{30\%} \approx 21kWh. \quad (1.9)$$

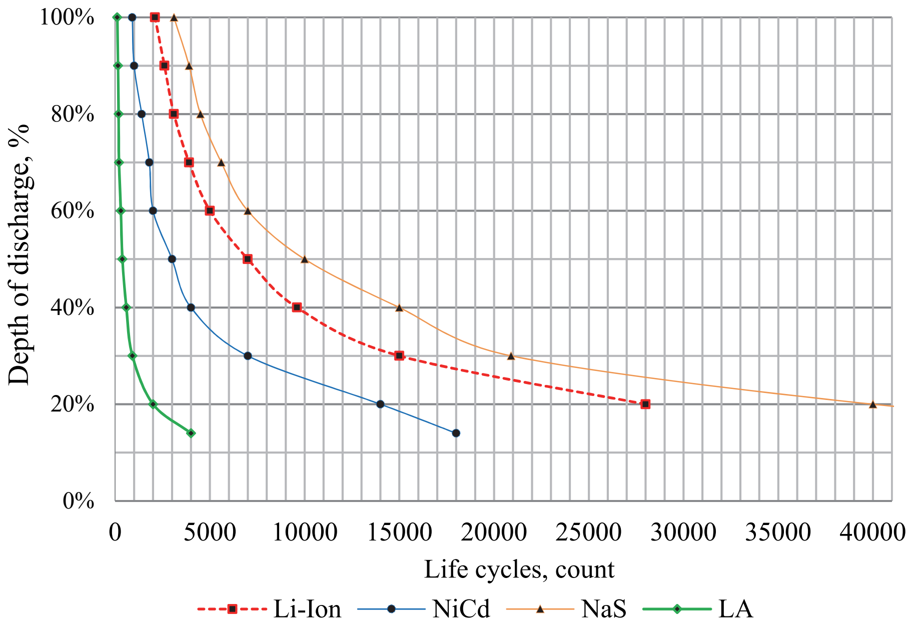

Figure 1.5 Life cycles and depth of discharge of different types of batteries [I]

As a result, instead of 7 kWh initial required capacity, with a theoretical 100% DoD, the BESS should be chosen with a capacity of 21 kWh and 30% DoD.

From the arguments in this chapter it can be concluded that open electricity market like NP allows even participation of small end customers in the energy market. Different programs of DSM like EE or DR can be used to achieve economic benefits from open energy market. In the region of Estonia, consumers have possibilities to purchase electricity from Elspot with day-ahead prices and Elbas - intraday real-time prices. With the use of DR programs and ES, the system can be valuable to an end user in terms of reliability and flexibility [35]. Assuming that a customer comfort level will stay unchanged and the consumption pattern is constant, the most suitable option for DR in a small-scale household is battery bank energy storage with energy capacity from 15 – 30 kWh. Typical load consumption pattern for weekdays and holidays is shown in Figure 1.6.

Basically, typical load consumption patterns can be presented in mathematical models like two dataset arrays with 24 elements. The first dataset represents a workday's and the second a weekend's consumption. The economic profit of DSM can be reached through taking advantage of the low price periods by importing more energy and storing it in BESS, while reducing the imported power during high price periods by supporting the load with the stored energy [V]. The algorithms based on day-ahead (DAA) and real-time prices (RTPA), provided in next chapter, could be implemented for this purpose in the Energy Management System (EMS), which includes BESS and other control devices. Feasibility of this system is analyzed in Chapter 4.

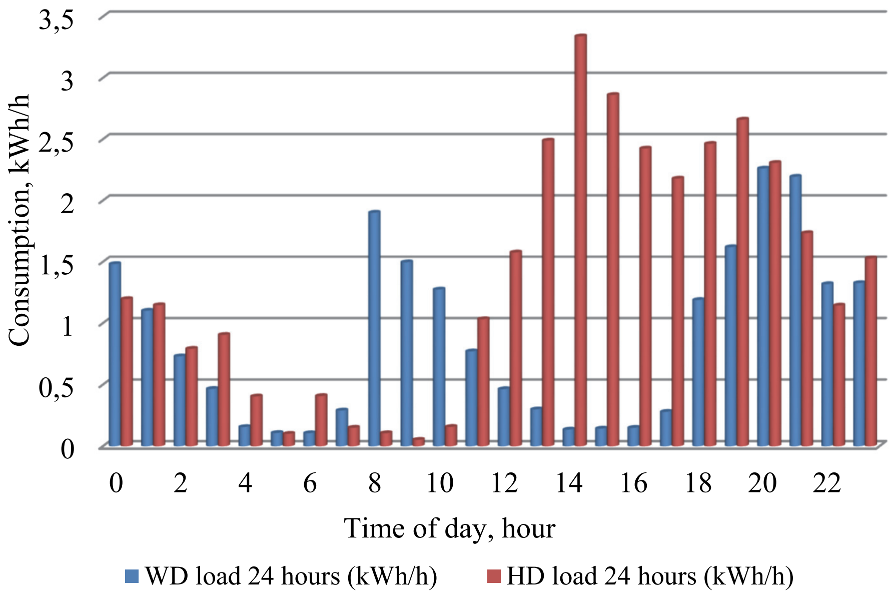

Figure 1.6 WD and HD load pattern for 24 hours [33]

2. RESEARCH AND DEVELOPMENT OF CONTROL ALGORITMS

2.1 Research of recent mathematical models for energy shifting within constraints of EMS

This chapter describes research work and development of the mathematical models for BESS in EMS. This is an essential task since existing models of other works do not fully match the constraints of the developed EMS. Furthermore, implementation of a mathematical model in a real EMS could confirm or disprove the hypothesis about the feasibility of EMS usage in the limits of Estonian energy market activity. This section is a compendium of articles [V], [VI] and [VII].

Recent developments include a number of new approaches to minimize electricity bills in households by using electric energy storage. Technical and economic literature on electric energy storage describes various storage applications that are partly overlapping [V]. In the scope of this thesis, the following optimization methods for DAA were analyzed: Model Predictive Control [36], deterministic approach, particle swarm optimization, linear optimization methodology, dynamic optimization, and the Taguchi Method [37] [38] [39] [40]. Due to the complexity in the implementation, only a few of them are suitable for use in household energy systems. Many approaches are inflexible for use without photovoltaic (PV) or wind turbines, which also makes them inoperable in households without solar or wind sources [VI].

It is the same here as with DAA, i.e. several RTP based control model implementations and descriptions can be found in different studies. One of the ambitious projects interconnected to the DR area is the EU FP7 project named EcoGrid EU [41]. It is developing and demonstrating a new market concept with a 5-minute time resolution, where the residential and commercial customers are responsive to imbalance pricing close to operation. The place of the EcoGrid time resolution project in the time scale of electricity markets is shown in Figure 2.1.

An approach with dynamic optimization of control method for BESS, including informative comparison to linear optimization, can be found in [42]; however, storage devices used there are much larger than ordinary household storages, and cannot be used by small participators. Multi-period energy with the reserve pre-dispatch model and the energy re-dispatch model for real-time operation were studied in [43]. The idea to use Home Energy Management Scheduler (HEMS) with three subsequent phases: real-time monitoring (RTM), stochastic scheduling (STC), and real-time control (RTC) can be found in [44]. However, it has been developed mostly to find the optimal way of scheduling the household appliances to minimize the cost of energy consumption. BESS in this system has no prior role. In [45], an electric vehicle (EV) is used in the role of BESS [45] and in [46] it is pointed out that there are multiple energy providers in the system and the customers need to determine not only the optimal energy consumption allocation at each hour, but also the optimal energy provider for each of them. Moreover, load scheduling optimization pseudo code of [47] was studied. On the other hand, it has restrictions in a household's application due to the photovoltaic energy source, which is not all the time obtainable.

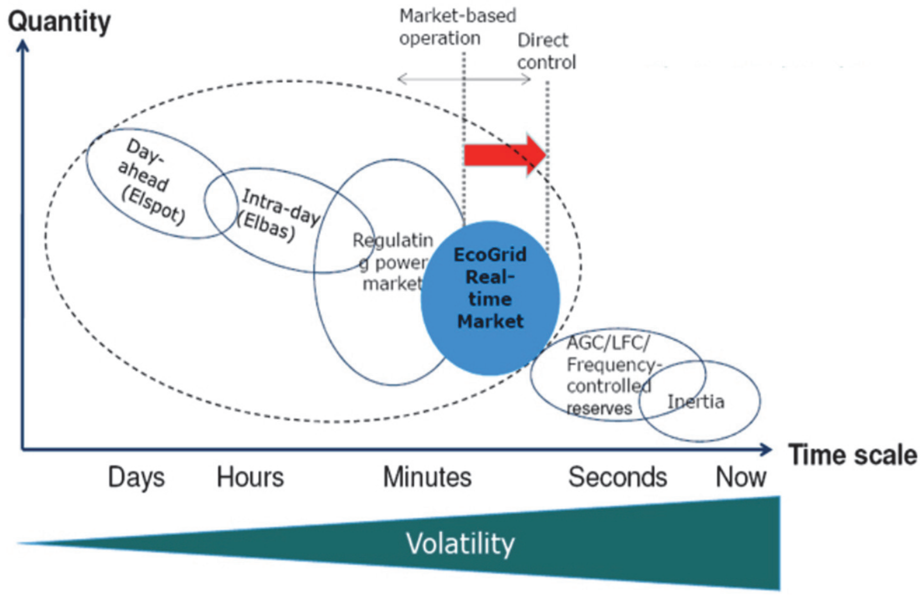

Figure 2.1 Time resolution EcoGrid project [41]

The main advantage and novelty of the algorithms, in the dissemination of the thesis, is in their simplicity. Also, they were partly tested with practical laboratory measurements, in accordance with EMS suitable for households. Mathematical functions for the DAA of EMS, as well as RTPA, were developed taking into account the theoretical model of a battery [II] [48]. Each algorithm has simplified sides, like constant consumption pattern, notwithstanding its responses to the main constraints of the EMS, which are:

- maximum DoD per battery charge discharge schedule (BCDS) cycle is 14%;
- SOC =100% of battery bank equals 21 kWh;
- maximum load consumption per hour is 3 kWh/h;
- battery charging current is limited at 15 A [VII].

The constraints of the battery have been taken into account in the research work: the SOC of battery has to be within the range of its minimum and maximum allowed limits. Similarly, the charging and discharging currents have to be within their boundaries [V]. For normal operation of the battery bank, the

DOD of deep cycle absorbent glass mat (AGM) batteries are recommended to be less than 30%. With EMS power limits, it is sufficient to use 14%; thus, 86% is considered the minimum value of the state of charge (*SOC*min) and 100% - the maximum value of the state of charge (*SOC*max). One of the most striking features of DAA and RTPA in this thesis is that they have discrete behavior and only three modes of BESS work. This is done with the help of decision variables *x1*, *x2*.The third mode is an idle mode, then *x1* and *x2* are equal to zero. Thus, other constraints of algorithms in EMS are:

$$\begin{cases} 0 \le P_C(t) \le P_C \max \\ 0 \le P_D(t) \le P_D \max \\ SOC\min \le SOC(t) \le SOC\max \\ \text{charging}: x_1 = 1, x_2 = 0 \\ \text{discharging}: x_1 = 0, x_2 = 1 \end{cases} \tag{2.1}$$

where P_C - the charging power; P_D - the discharging power, and *SOC(t)* - the state of charge of energy storage at the end of time slot *t*; $P_C max$ - maximum value of charging power; $P_D max$ - maximum value of discharging power [VI]; *t* - the time slot, which can differ according to DAA or RTPA.

2.2 Development of day-ahead price based control algorithm

DAA has been developed as a first algorithm for EMS and NP Elspot and it uses forecasted electricity prices for the next day to find the most profitable BCDS. It is based on the loop optimization routine and takes part in the spot market 24 h prior to the delivery [49]. The time period consists of *T* timeslots *t* with *t* = 1...*T*, where *T*=24 hours. The daily sum cost $C_{tot=24h}$ (2.2) without the use of BESS, considering only forecast prices and conditions (2.3) is [V]

$$C_{tot} = \sum_{t=1}^{T} (P_{grid}(t) \cdot Fp(t)), \tag{2.2}$$

$$\begin{cases} P_{grid}(t) > 0 \\ P_{grid}(t) = P_{load}(t) \end{cases}, \tag{2.3}$$

where P_{grid} - power from the grid; P_{load} - load consumption; *Fp* - the forecasted electricity price in €/kWh [VI].

During the operation, storage level at the end of each period is determined by the SOC of the previous period and, certainly, the charging or discharging operation in this period. It is shown in (2.4) [VI]:

$$SOC(t) = SOC(t-1) + x_1 \cdot \eta_C \cdot P_C(t) - x_2 \cdot P_D(t), \tag{2.4}$$

With battery parameters and values, HMI system searches for profit by using BESS. The algorithm sorts all the hours by price, which will give an array row with descending price as a key element. After that it calculates the possible amount of discharge hours, the total load of which corresponds to maximum DoD of EMS, allowed by the setpoint. These criteria for selection of the algorithm are presented in (2.5) [VI]:

$$\begin{cases} Fp(0) > ... > Fp(d) > ... > Fp(23) \\ \sum_{d=0}^{n} P_{load}(t(d)) + P_{load}(t(23)) \leq P_{CMAX} \\ \sum_{d=0}^{n} P_{load}(t(d)) \leq P_{DoD} \end{cases}, \tag{2.5}$$

where the first row - a sorted price series from max to min value Fp_{max} -> Fp_{min}, which means that array's element with index 0 has the highest price and with index 23 has the lowest price for the next 24 hours. The second row selects for discharging only hours, the total sum of power consumption of which does not exceed DoD allowed power. The count of the discharging hours is determined by an *n* variable [VI]. It can be found with an auxiliary index variable *m* by (2.6):

$$\begin{cases} \sum_{d=0}^{m} P_{load}(t(d)) \leq DoD \\ n = m + 1 \end{cases}. \tag{2.6}$$

To achieve correct load distribution in the array, the sort function is called, which merges the forecast prices with the 24-hour load array [V]. Final function of DAA calculates energy demand for hours with the highest price, starting from *Fp*(0), which matches the allowed DoD limit and calculates possible profit for that day. Thus, the day cost with the use of DAA C_{DAA} from (2.7) is as follows:

$$C_{DAA} = \sum_{d=n}^{22} (P_{load}(t(d)) \cdot Fp(d)) + \left(\sum_{d=0}^{m} P_{load}(t(d)) + P_{load}(t(23)) \right) \cdot Fp(23) \tag{2.7}$$

and the day profit *DayP* is calculated from (2.8) by subtracting DAA day cost from the day cost without EMS:

$$DayP = C_{tot} - C_{DAA}. \tag{2.8}$$

All equations (2.2 – 2.8) compose the mathematical model of DAA. To implement the model to the programming environment, firstly it was designed with Unified Modeling Language (UML) [50]. Figure (2.2) illustrates the logic of the DAA in the UML activity diagram.

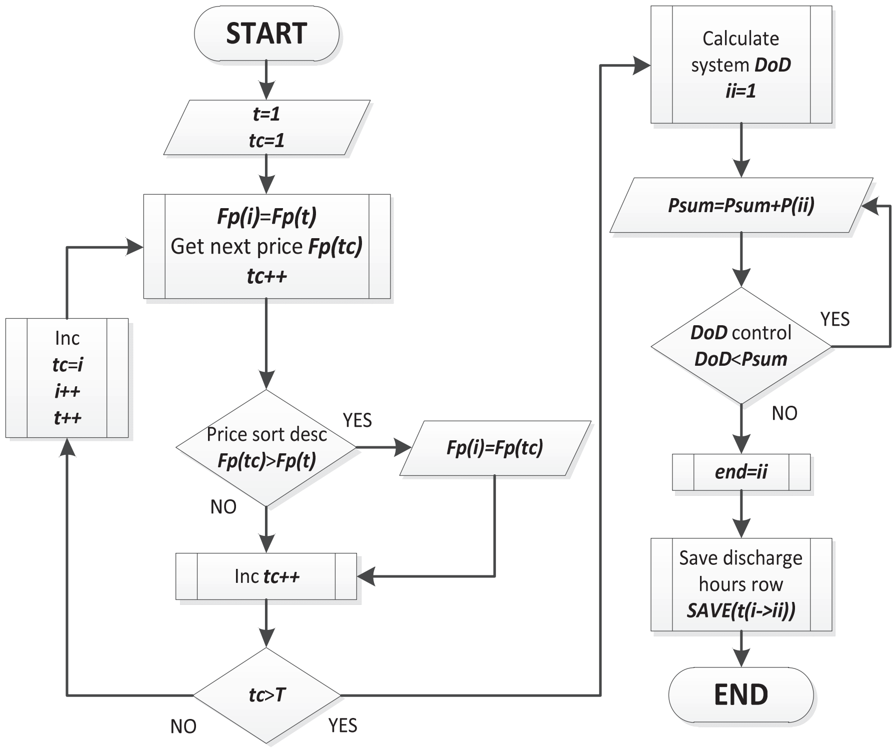

Figure 2.2 DAA UML activity diagram

According to UML, the DAA software implementation was created in two software environments: Visual Basic (VB) and Matlab Simulink. The main theoretical calculations were made in VB; however, their results found confirmation in Matlab simulations afterwards [51]. View of the Simulink model is presented in Figure 2.3.

An example of DAA work with distribution of the prices and the load curve is shown in Figure 2.4. It shows actual work of EMS with DAA on the date 12.11.14. The hours with load consumption equaling zero mean that energy for the load was taken from the batteries. Increased load curve values at other hours mean that additional load went for battery charging [VI].

According to (2.2), the total cost of electricity for a day on 12.11.14 without use of EMS was 37 EURO cents (¢) and the cost of electricity according to (2.7) with the use of EMS was 30 ¢, which makes a total saving of the consumer from (2.8) around 7 ¢.

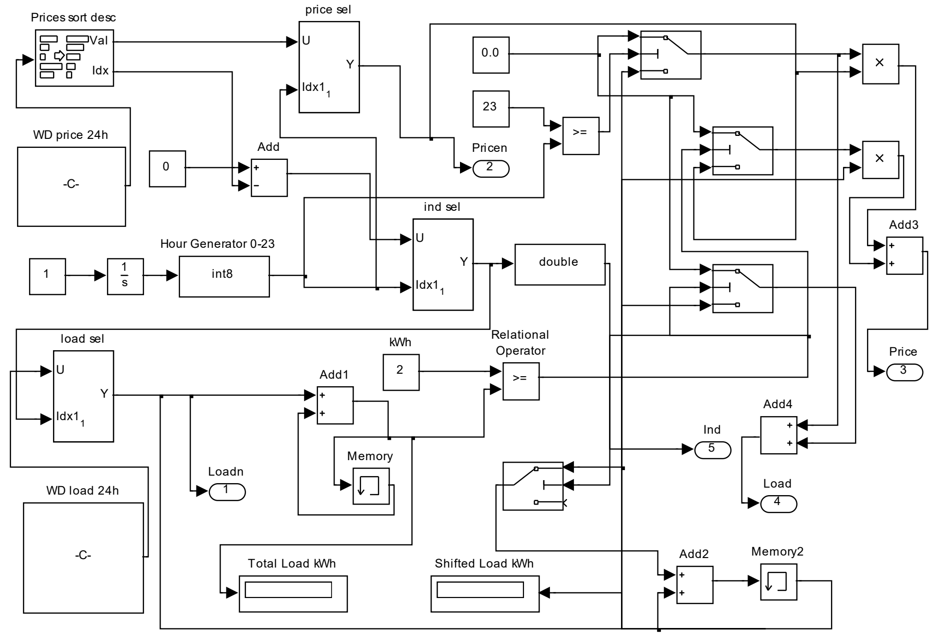

Figure 2.3 Matlab Simulink model of DAA [51]

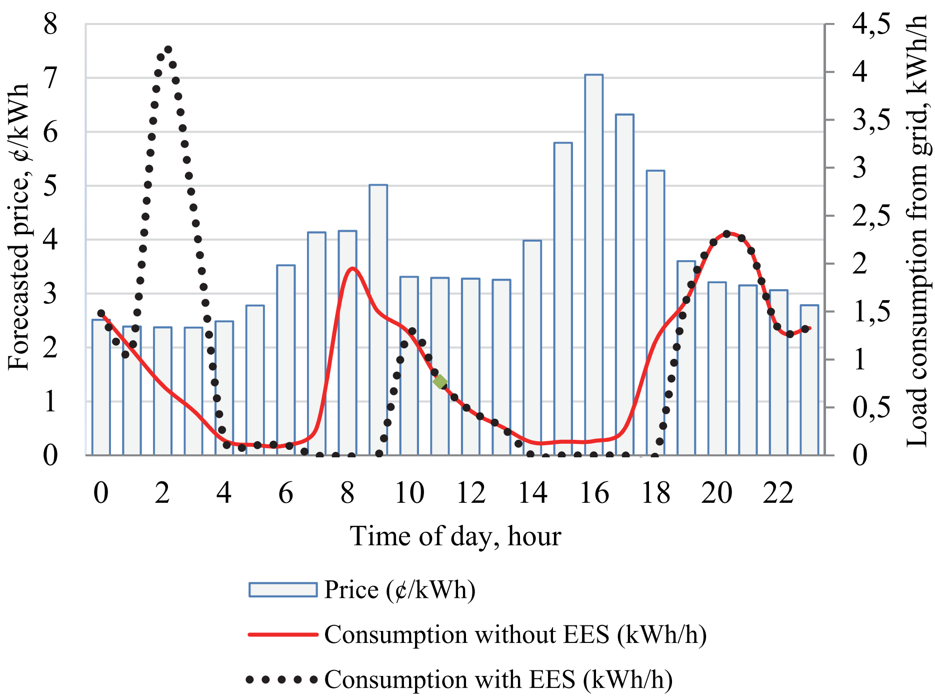

Figure 2.4 Load and prices distribution with the use of DAA and EMS for 12.11.14

2.3 Development of real-time price based control algorithm

Here a RTP energy market NP Elbas is observed with a developed real-time price based control algorithm for EMS. It has flexible functionality of the BCDS during unclear stochastic price movement at one hour time periods before the power is delivered [52]. Only the price forecast data and price history are considered along with household's energy consumption. Thus, RTPA forecast procedure analyzes the past of the energy price for a predefined back-time period and optimizes the BCDS to bring the highest profit to the end customer. This revenue could be achieved through energy price arbitrage - taking advantage of price differentials in the open electricity market with the BESS [VII]. A major difference between DAA and RTPA is that with RTPA only the current price for the next beginning hour is available, and the prices for future periods of time are unknown, it is important to use tuned optimized parameters and price history to forecast market trend behavior and to find out most profitable time-slot (hour) for charging or discharging of BESS [VII].

The system analyzes *n* day history of hourly prices. The developed algorithm finds minimum and maximum prices (local extremes) for each day in the described time range. These local extremes are used to calculate minimum level L_{min} price and maximum level L_{max} price for a current hour. To avoid rapid change of stated levels, the values are smoothed by a simple moving average (SMA) function. To enhance probability that the price of the beginning hour will reach and cross either L_{min} or L_{max}, also minimum level is increased by margin H_{min} (2.9) and maximum level is decreased by margin H_{max} (2.10):

$$L_{\min}(t) = \frac{\sum_{o=1}^{n} Fp_{\min}(t-o)}{n} + H_{\min}, \tag{2.9}$$

$$L_{\max}(t) = \frac{\sum_{o=1}^{n} Fp_{\max}(t-o)}{n} - H_{\max}, \tag{2.10}$$

where Fp_{min} - the array of daily minimum price and Fp_{max} - the array of daily maximum price of *n* days. The flexibility of the algorithm allows to optimize parameters: *n*, H_{min} and H_{max}, to achieve the maximum profit of the system. Basically, the algorithm has three states: charging, discharging and idle stage (2.11) [V]:

$$\begin{cases} Fp(t) \geq L_{\max}(t) \wedge SOC(t) > SOC\min \rightarrow x_1 = 0, x_2 = 1 \\ Fp(t) \leq L_{\min}(t) \wedge SOC(t) < SOC\max \rightarrow x_1 = 1, x_2 = 0 \\ Fp(t) > L_{\min}(t) \wedge Fp(t) < L_{\max}(t) \rightarrow x_1 = 0, x_2 = 0 \end{cases}, \tag{2.11}$$

where x_1 and x_2 are charge/discharge state variables according to (2.1).

The total cost of energy for a particular time period T with the use of RTPA C_{RTPA} will be calculated as follows (2.12) [V]:

$$C_{RTPA} = \sum_{t=1}^{T} (P_{load}(t) \cdot Fp(t) - (P_{load}(t) \cdot Fp(t) \cdot x_2) + (P_C(t) \cdot Fp(t) \cdot x_1)), \qquad (2.12)$$

Similar to DAA, the mathematical model of RTPA was designed with UML and afterwards implemented to the programming environment. Figure (2.5) illustrates the logic of the RTPA in the UML activity diagram.

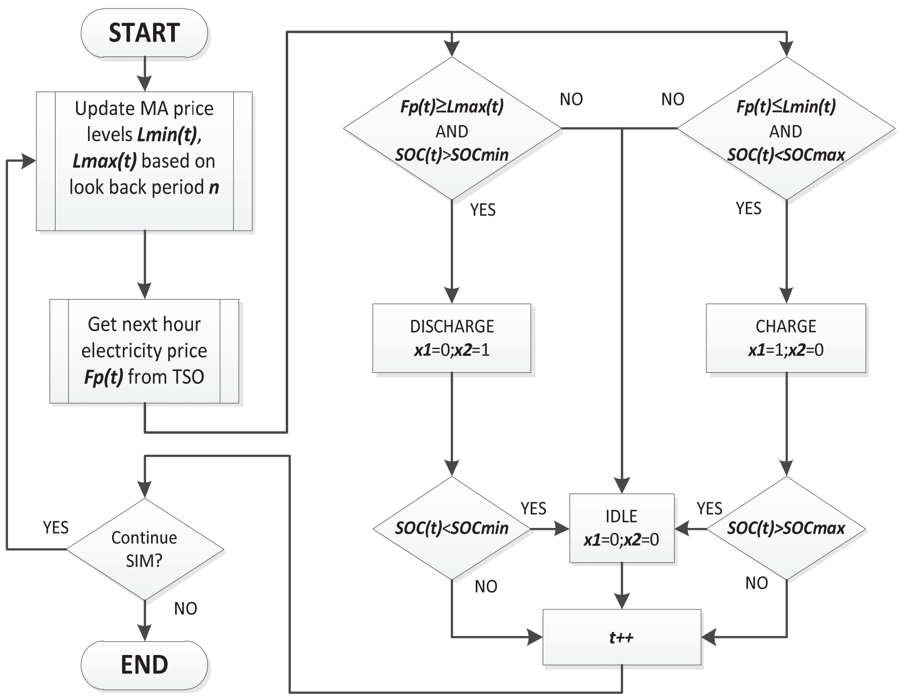

Figure 2.5 RTPA UML activity diagram

Later, RTPA was transferred from UML into VB and Matlab Simulink software environments. Theoretical calculations were made in both systems. View of the Simulink model is presented in Figure 2.6.

The result of the total energy cost can be optimized by tuning system parameters in a simple loop optimization. The goal of optimization is to find out values of parameters: L_{min}, L_{max}, H_{min} and H_{max} which will provide maximum profit Pr according to (2.13):

$$\Pr = MAX\ (\sum_{t=1}^{T} (C_{tot} - C_{alg})), \qquad (2.13)$$

where the key factor is the spread between the total cost of energy consumption (without EMS) and the cost calculated with the use of RTPA and EMS [VII]. Most beneficial parameters for the RTPA found in the scope of this thesis based on the loop optimization are as follows:

- SMA period $n = 2$ days for minimum price array,
- SMA period $n = 6$ days for maximum price array,
- minimum level margin $H_{min} = 0.2$ ¢,
- maximum level margin $H_{max} = 1.6$ ¢.

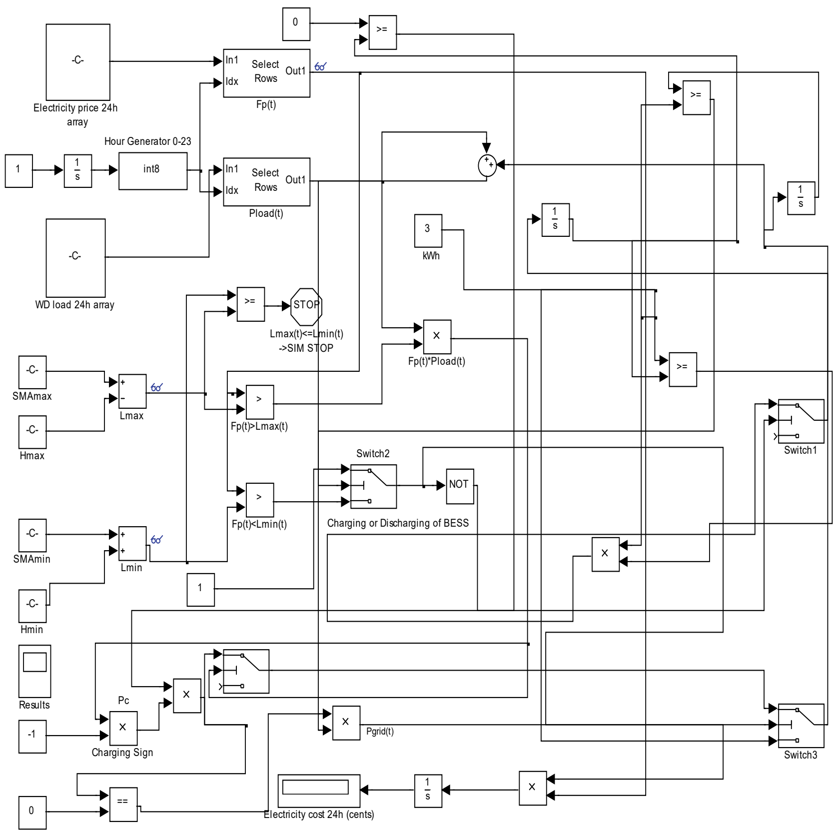

Figure 2.6 Matlab Simulink model of RTPA [51]

Historical period of the NP prices for optimization was taken from the beginning of the year 2014 up to the end of the year 2015. An example of RTPA work with the distribution of the prices and the load curve is shown in Figure 2.7. It shows theoretical work of EMS with RTPA on the date 12.11.14 [VII]. If the current electricity price (blue column) crosses above the maximum price level Lmax (orange line), the discharging mode of EMS is activated. Load consumption curve (dotted black line) is zero at that time. When the electricity price crosses below the minimum price level Lmin (green line), EMS starts to charge the batteries. However, RTPA also controls the current SOC value, charging and discharging of the BESS is possible only within permitted (2.1) value limits. If the electricity price is flat between the levels, the EMS system has idle mode, meaning that load consumption is fed directly from the grid [VII].

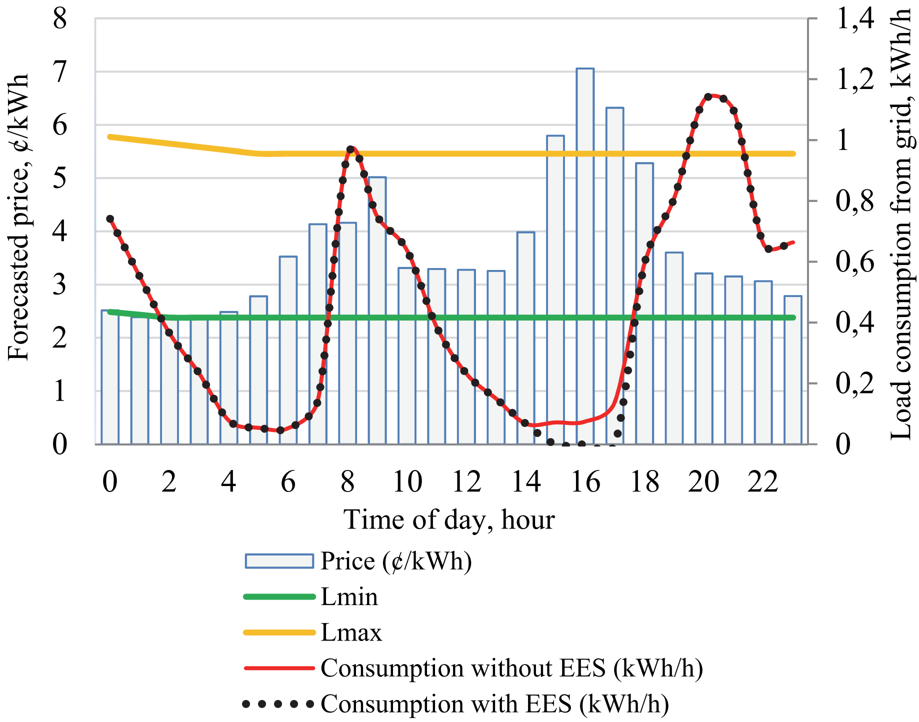

Figure 2.7 Load and prices distribution with the use of RTPA and EMS for 12.11.14

According to (2.2), the total cost of electricity for the day on 12.11.14 without the use of EMS was 37 ¢ and the cost of electricity according to (2.12) with the use of EMS and optimized parameters was 35 ¢, which makes the total saving of the consumer from (2.8) around 2 ¢.

2.4 Evaluation of BESS control algorithms

First, based on the above, it should be stressed that DAA completes one battery charge-discharge cycle per each day in any event. Taking into account that profit per day by the use of EMS is the main score rate parameter, it is concluded that RTPA does not provide battery charge or discharge cycle every day. The conditions for charging or discharging of BESS depend on the current hour price, the history of price and SOC. This means that on some periods or days, BESS may only charge, discharge or be in idle state (load is fed directly from the grid). On the other hand, to simplify comparisons, average day profit is calculated from the total profit achieved by all days of the simulation. The most informative description of the new RTPA is the profit or loss gained by it when compared to the DAA result and regular (without EMS) energy use in household [VII]. The profitability of each agorithm is valid if the condition (2.14) is true and (2.15) [53] shows the profitability of the algorithm,

$$C_{alg} < C_{tot} , \tag{2.14}$$

$$\alpha = \frac{100 \cdot (C_{tot} - C_{alg})}{C_{tot}} , \tag{2.15}$$

where C_{alg} - the total cost of energy by the use of a particular algorithm for a particular time period (24 hours, week, month etc); C_{tot} - the total cost of energy for the same particular time period; α - relative reduction of the energy cost.

Theoretical results of DAA and RTPA during the time period of 2014 – 2015 are compared in Table 2.1 and Figure 2.8.

Table 2.1 Energy cost with different algorithms

Date	**Results of Algorithms**		
	No EMS, cost (€)	***DAA, cost (€)***	***RTPA, cost (€)***
2014	501	420	445
2015	403	321	327
Total 2014-2015	904	741	772
Day average	1.23	1.01	1.05
Day profit (*DayP)*	0	0.22	0.18
		DAA (%)	***RTPA (%)***
Profit for 2014		16.2	11.7
Profit for 2015		19.1	18.1
Total 2014-2015		17.6	14.9

Differences in the result are varying for different years. In 2014, as compared to RTPA, the result of DAA was approximately 4.5 percent point better. In 2015, the profit difference between two algorithms was only 1 percent point. It is evident that an optimized RTPA is still less profitable than DAA. Average difference in the result between algorithms for a two-year period is only 3 percent point, which is a relatively good result for RTPA designed for stochastic price prediction.

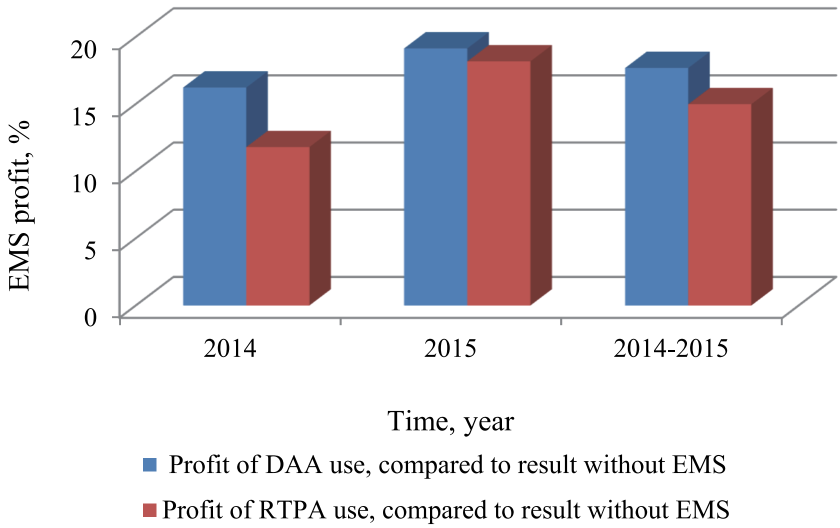

Figure 2.8 Profit of DAA and RTPA in comparison with the cost of energy without EMS

3. RESEARCH AND DEVELOPMENT OF THE NEW ENERGY MANAGEMENT SYSTEM

3.1 Design of the New Energy Management System

3.1.1 Introduction to the basic concept of the Energy Management System

This chapter focuses on the research and development of the small-scale EMS and describes the practical part of the thesis task. This system is essential to confirm the theoretical part in the limits of Estonian energy market activity. This section is a compendium of articles [V], [VI] and [VII] and takes into consideration the issues described in the previous chapter.

As was mentioned above, BESS in the distribution grid system is similar to a hybrid system, which means that load demand is met by the grid power and/or power of the BESS. Control and management of that power is done by EMS. According to [54], EMS is defined as a system of computer-aided devices used by customers of electric utility grids (smart grids) to monitor, control, and optimize the performance of the generation, transmission and/or consumption system. Energy management systems are also often commonly used by individual commercial entities to monitor, measure, and control their electrical building loads. EMS can be used to centrally control devices like: Heating, Ventilation, Air Conditioning (HVAC) units and lighting systems across multiple locations. EMS is able to provide metering and monitoring functions that allow facility and building managers to gather data and insight that allows them to make more informed decisions about energy activities across their sites [54]. Design of EMS is a major challenge facing the technology. Currently, no standard platforms are available for the design and implementation of EMS. Even integration of EMS solutions from different vendors is difficult since every company provides its own unique systems, configuration and control strategies [55]. Generally, EMS for households or Home EMS (HEMS) has several subcategories illustrated in Figure 3.1.

These categories are:

1. Sensing devices: Household sensors relevant for EMS application are for the detection of current, voltage, temperature and other parameters. They sense the desired parameters at different locations and send the signals to a centralized system. Using these parameters, smart appliances can be monitored, controlled or scheduled to operate at desired periods.
2. Measuring devices: Most often, what can be measured can be controlled. Gas, water and electricity meters are the main measuring devices for households.

3. Smart appliances: Domestic appliances with integrated intelligence and communication systems which enable the devices to be monitored and controlled (switched on/off) remotely. Smart appliances provide residential customers with insight into their energy use, enabling energy-efficient and eco-friendly behavior.
4. Enabling Information and Communications Technology (ICT): ICT is the link connecting the sensor, meters and devices to the monitoring or control unit. Both wireless and wired communication technologies are developed for the integration of various domestic devices. Wi-Fi, Zigbee (based on the IEEE 802.15.4 standard, known for its low cost, power consumption and data rate) [56], HomePlug and Z-wave are some of the leading technologies facilitating home area networks [55].
5. Main part of EMS – compilation of different solutions for control of other devices.

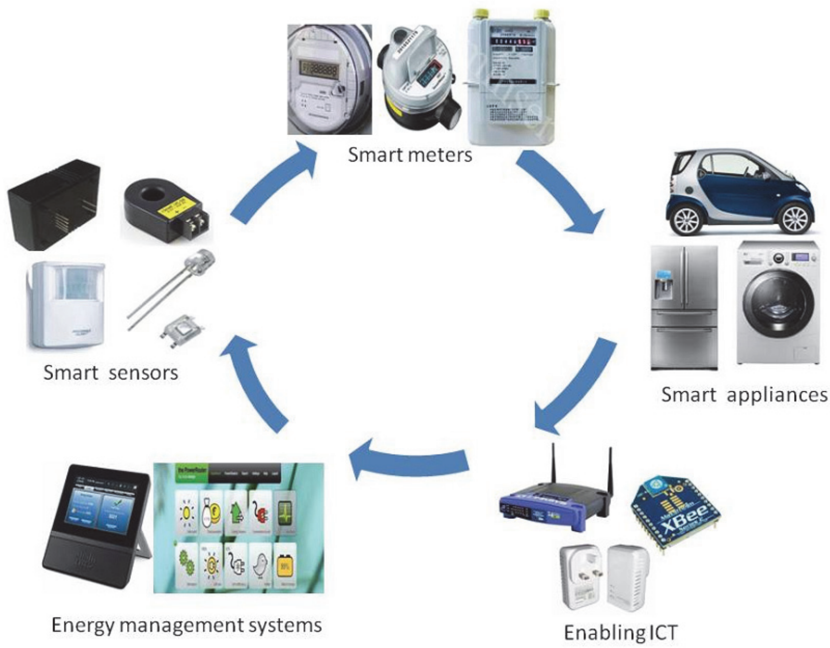

Figure 3.1 Fundamental subcategories of a home energy management system [55]

In the energy management principles, software platforms and embedded intelligence adopted in EMS solutions differ with each manufacturer. Currently, several EMS systems for households are under development by leading vendors, such as Intel, Siemens, Control4, Hitachi, Google, Microsoft, Cisco [55] [57]. But no fit-for-all solutions are available, as various developers focus on different aspects. In general, home energy management can offer the following functionalities:

- *Informative* overviews about energy usage data in various graphical forms (Human Machine Interface, Graphical User Interface) to the users;
- *Automated* actions which offer customer options to set priorities and wishes for the operation of household appliances and/or local generations;
- *Advanced* functions: this includes information, automation and control;
- *Integrated* systems with all the features of the advanced functions [55].

Nevertheless, from the consumers' viewpoint, the essential goal of home EMS is to reduce their total electricity payment while satisfying their needs as well. Specifically, the optimal strategy provided by EMS is to modify and adjust the control settings of each load or appliance at home in accordance with the variation of price, the preferred comfort level, etc. These functionalities can be expressed through an abstract design of EMS shown in Figure 3.2, where three main parts of EMS design are: Data Collecting, Processing and Controlling [58] [59].

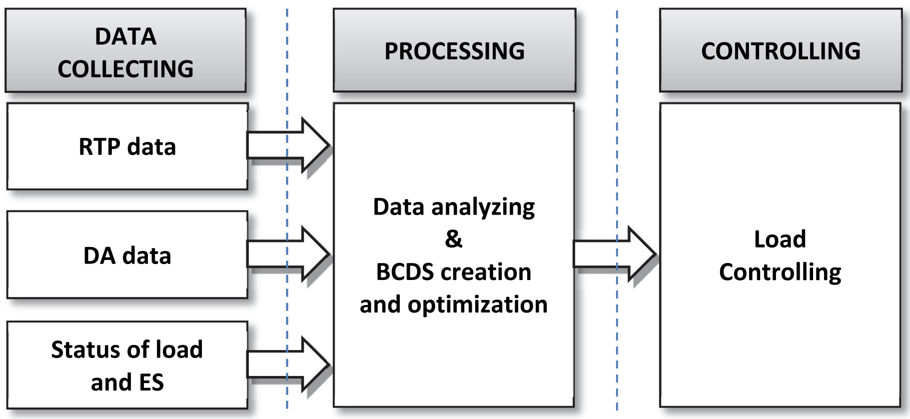

Figure 3.2 Expected major functions of the designed EMS

Numerous studies have described EMS for homes and households and their implementation in grids. However, apart from commercial ready systems from vendors, most of the presented systems are prototype systems. Some of them are focused entirely on the hardware designed and do not take into account the machine learning algorithms required to achieve the load management and price prediction. On the other hand, many simulation studies in the literature rarely give a HEMS hardware design although they consider an individual issue from the "software" side, such as machine learning algorithm, dynamic price responsive mechanism, and other challenges in practical applications [60]. The development of a functional EMS system requires a new approach from existing systems. In regard to the numerous models currently in the market, customers are usually unaware of their presence and are thus misinformed about the functionality of EMS. Consumers must be aware of EMS before they become viable for domestic use. Some of EMS studies were discovered during projecting and designing of EMS. One approach has an interesting design, however it changes the comfort level of the end customer by the control of the HVAC system of the house [61]. The largest part of them is narrowed by the use of PV and EV in the local grid [62] [63] [64] [65] [66] [67] [68]. Many EMS projects have ZigBee [56] implementation, which is impossible for EMS designed in this thesis research. In this study, the main differences resulting from the design of EMS as compared to other systems are as follows:

- high flexibility of design and usability with different types of load (not only HVAC);
- no need for factors such as EV and PV source in the algorithm in the grid, which makes them more universal;
- no need for special measuring devices (Smart Meter) and special communication standards (ZigBee);
- all electricity prices are taken from the Internet; no special contract with TSO required,
- no need for special smart sensors.

Moreover, as different from some reported simulation studies, an overview of real hardware is presented here.

3.1.2 Design of the new Energy Management System

Based on the three main parts of EMS described above, the design of EMS has to provide main functionality for these parts. Thus, the primary functions of the designed EMS are:

- to collect useful information and other messages, such as electricity price, status of load and battery;
- to generate the optimal strategy or BCDS by analyzing the collected data;
- to modify or adjust the load supply on the automatically generated BCDS by the control algorithms [58] [60].

The main requirement concerning these functions is that they have to interchange data between the parts of EMS. It can be done by the help of the network of the EMS with different task layers described in [63] and represented in Figure 3.3.

The layers can be described as follows:

- Physical layer: The information equipment, such as power devices and sensors, are deployed in this layer. This equipment is used to collect different types of perception information which include, but is not limited to the battery SOC status of ES, Inverter workflow, and power consumption of the household. This reception information is transmitted through the gateways to the subsequent network layer [63].

- Network layer: Wired (e.g., power cable, RS-232) and Internet communication are used to complete the perception information transmission between the components of EMS. The main concern of this layer is the data routing and proactive information push mechanisms [63].
- Application service layer: All perception information obtained from the network layer is stored, processed, and analyzed in this layer. For instance, ES SOC, electricity price, and retail prices of electricity, uploaded by the gateway are stored in the database platform. The price-based energy dispatch strategy is performed at the application platform to manage the energy flow between the household loads and the ES [63].

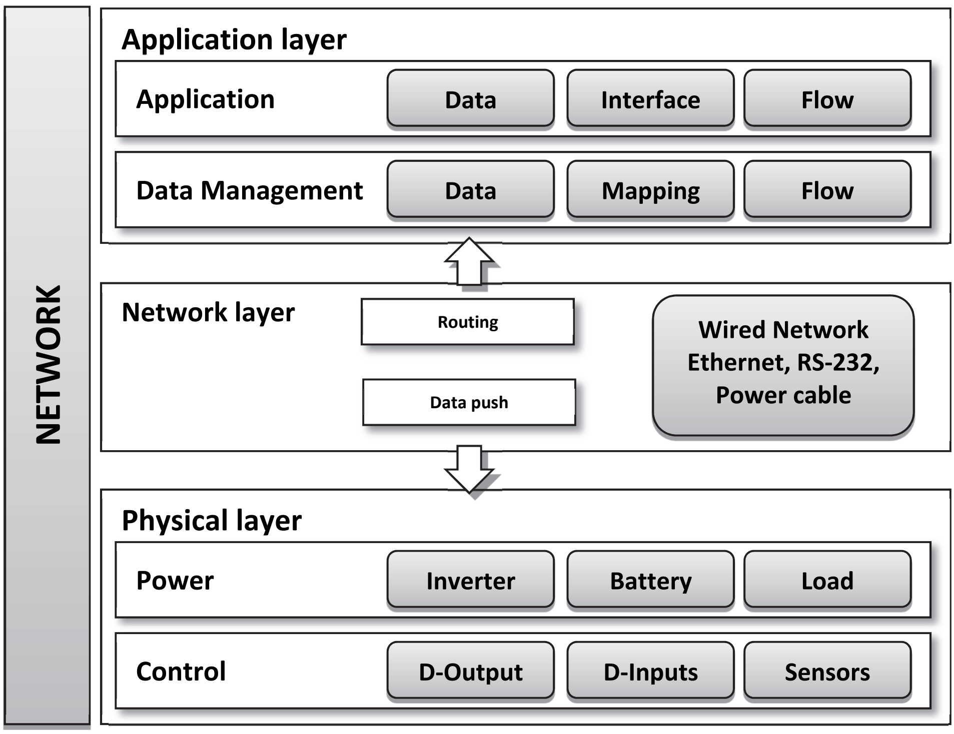

Figure 3.3 Architecture of the layers for the proposed EMS structure [63]

In this thesis, according to general requirements of the EMS concept and layers' structure, the new EMS was developed and designed in laboratory. Furthermore, it was used for testing purposes of the designed control algorithms. It uses a deterministic approach that ensures an optimal use of BESS and fulfills load demand supply at the lowest cost, at the same time considering the limits of the system [V]. Figure 3.4 illustrates the new EMS structure.

Concerning the actual constraints of the laboratory grid, the connected battery bank does not feedback the grid and the storage is used only to support the load demand. EMS constraints make the load inflexible with respect to the energy cost, but charging and discharging operations of EES are still controllable by the system algorithm. Operation parameters of an EMS, such as minimum and maximum energy storage capacity, discharging current limit, charging current limit, and charging efficiency, were considered during control software development [VI] [36].

The hardware part of the EMS is a compilation of different subsystems with various tasks. It consists of four parts:

- Personal Computer (PC),
- Programmable Logic Controller (PLC),
- Power Unit (PU),
- Load [V].

The components of the EMS were selected because of the price/features relation. In other words, it was the most reasonable selection at the time of installation.

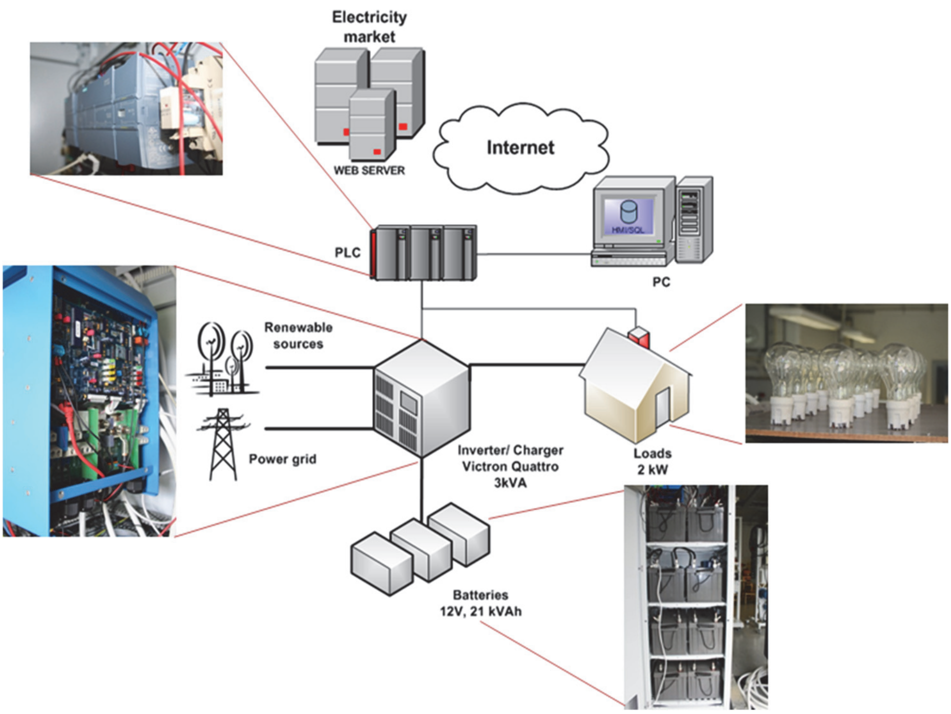

Figure 3.4 Design and structure of EMS [V]

3.1.3 Power Unit with Storage

The PU is a battery inverter and a charger combined in one unit. The basic element of this device is a 3 kW Inverter of Quattro series (manufactured by Victron Energy) [V]. PU is needed to provide connection between the grid and batteries of EMS. Also, it integrates power electronics control of batteries on the physical layer. Off-grid power systems with this unit can operate multiple electrical loads without overloading the alternating current (AC) power source, and deliver continuous uninterrupted power at power failure [69]. Each Quattro is a true sine wave inverter, meaning clean power for sensitive electronics. It is also a sophisticated battery charger that features an adaptive charge technology [V]. The EMS storage consists of a battery pack with deep cycle AGM batteries 12 V DC at a total capacity of 440 Ah in pairs, making a total voltage of 24 V, a capacity of 880 Ah. In these batteries, the electrolyte is absorbed into a glass-fibre mat between the plates by capillary action. According to [70], AGM batteries are more suitable for short-time delivery of very high currents (engine starting) than gel batteries. Total stored energy of BESS amounts to 21 kWh. This capacity has been selected with a particular DoD to cover simulated household's load demands [VII]. The inverter acquires all the required values from batteries via the precision Battery Monitor (BM). The BM is a device that monitors PU battery status. It measures battery voltage and battery current constantly and uses this information to calculate the actual state of the charge of the battery bank. The last basic element of the PU is the Digital Multi Control panel (DMC), which allows limiting grid input current and monitoring basic status of the inverter [V].

3.1.4 Auxiliary Control Unit

The PLC has the role of an auxiliary device in EMS to provide control between PU and Human Machine Interface (HMI). EMS has PLC with Siemens central processing unit (CPU) of S7-1200 series. These types of controllers operate in a variety of industry automation and household applications. The controller was chosen because of connection features of this controller [V]. It combines a microprocessor, an integrated power supply, input and output circuits, built-in PROFINET, high-speed motion control inputs/outputs (I/O), and on-board analog inputs in a compact housing to create a powerful controller. The CPU monitors the inputs and changes the outputs according to the logic of the user program downloaded to CPU [71]. This smart PLC makes on/off switching of the load groups during working hours. It was made to simulate a real load of a typical household consumption during 24 h. Therefore, the CPU of the controller has two databases with 24 records each, corresponding to 24 hours of the typical average load consumption in households.

The main task of the PLC is to control the BCDS according to the profile data transferred from the PC [V]. For the testing purposes, the system contains 15 bulbs with a total power of 1.5 kW to imitate household consumption. The typical household load consumption is around 3 kW, but it was scaled two times lower to match EMS power limits. The PLC interpolates load values in accordance with a 24 h load [VI]. It activates totally 4 load groups with 4 digital outputs:

- group 1 – 1 bit – 1 bulb digital output DQ0.4
- group 2 – 2 bit – 2 bulbs digital output DQ0.5
- group 3 – 4 bit – 4 bulbs digital output DQ0.6
- group 4 – 8 bit – 8 bulbs digital output DQ0.7

Each bit activates 1 bulb with 100 W power. Therefore, the entire load of 1500 W could be simulated by PLC by activating four load groups, which correspond to 15 bulbs. Since PLC is considered as a low voltage control device, switching of a load group considered as a power device takes place through power contactors. Almost all hardware devices could be controlled with the help of special software developed for EMS.

3.2 Software of EMS and Data Flow between Subsystems

3.2.1 Introduction

Main objectives in the new system design and development were to solve integration problems, where the main tasks are machine-machine and human-machine integration problems, which include solution of hardware-software, software-software compatibility and integration problems. Human-machine interaction must be taken into consideration, which influences safety, security and reliability of the systems. For that reason, interface between human-machine has an essential role in the entire EMS system [72]. Evidently, human-machine interface application in this thesis work has been designed as the main part of software development and also a major control part of the EMS. Similar to general EMS design, there are no typical platforms or standards for the HMI design of EMS at the moment. However, new design often requires the development of unique hardware and software solutions or applications. Furthermore, system integration of good graphical user interfaces (GUI) design involves determining end user needs, testing for simple and effective usability, focusing on functionality, concentrating on display consistency, ensuring ease of use, using color effectively, using colors with ideal contrast ratios, balancing the visual harmony of the display, making sure the text is readable [72]. Finally, it is necessary to have a friendly and easy-to-use interface to change settings at the consumer side. Since ordinary consumers could be unfamiliar with the operation of electricity markets or power systems, GUI has to incorporate an easy-to-use interface to increase awareness of the EMS by demonstrating how the system enables the users save their money and highlighting the benefits of the system as a whole [60]. The designed HMI has the main role in the data flow of the entire energy system. According to the general EMS concept, it fulfills two tasks of two EMS subsystems: data collection and processing. With the help of PLC it is responsible for control of all EMS subsystems. Thus, the control of the workbench is divided into two parts: the calculation/processing in the HMI and executing/running in the PLC. In an active automatic mode, software provides particular steps in the control sequences [V]:

- sends a request for the forecasted NP energy prices from TSO Elering for the next time period at 00:00 EET (Eastern European Time);
- processing function of the electricity market price (PriceGrabber software) saves fetched data to a special file;
- optimization part in the HMI application processes price and load data for the next 24 hours from special files and creates a new BCDS;
- the new BCDS is being transferred to PLC;
- control part in PLC logic starts to switch modes of BESS, thus charging and discharging batteries according to the electricity market price;
- PLC switches load groups according to workday or weekend day consumption pattern [V].

Figure 3.5 illustrates the concept of EMS and the data workflow inside the system.

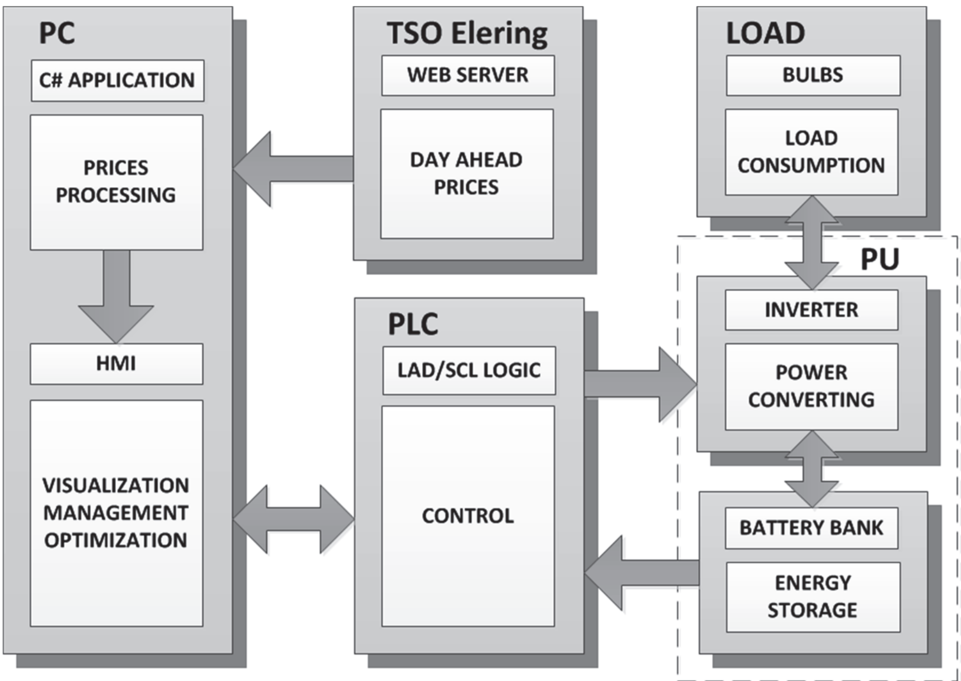

Figure 3.5 Main system parts and data flow directions [V]

3.2.2 PLC software

The main software programs have been developed for PLC and PC. The PLC program was designed in Siemens Totally Integrated Automation (TIA) Framework and presents the mix of the functions written in Ladder Logic (LAD) and Structured Control Language (SCL) [V]. The screenshots from LAD logic are shown in Figure 3.6.

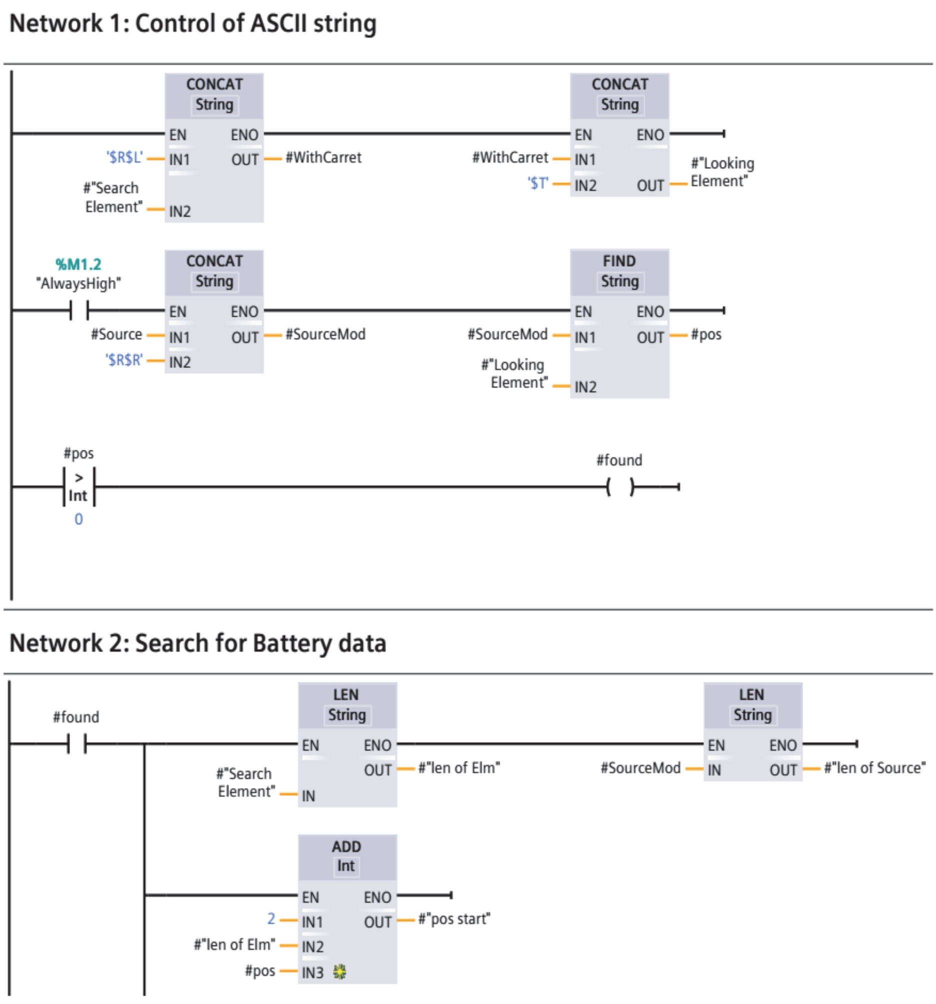

Figure 3.6 LAD language of EMS PLC logic

SCL was used because of some complicated communication functions that cannot be implemented in pure Ladder Logic. SCL is a high-level programming language based on PASCAL. The language is based on DIN EN 61131-3 (international IEC 1131-3) and provides convenient instructions for controlling the program: creating program branches, loops or jumps [73]. With the help of this language, the program implements communication between the CPU and the Battery Monitor with the help of the BM protocol. Communication part requests the main parameters of the batteries and converts them to American Standard Code for Information Interchange (ASCII) data with service characters. CPU accepts this protocol on the RS232 layer [V]. In telecommunications, RS-232 is a standard for serial communication transmission of data. It formally defines the signals that connect a DTE (data terminal equipment) such as a computer terminal and data circuit-terminating equipment (DCE) or data communication equipment, such as a modem [74].

The relation of the main data flow and the modules in PLC software is shown in Figure 3.7.

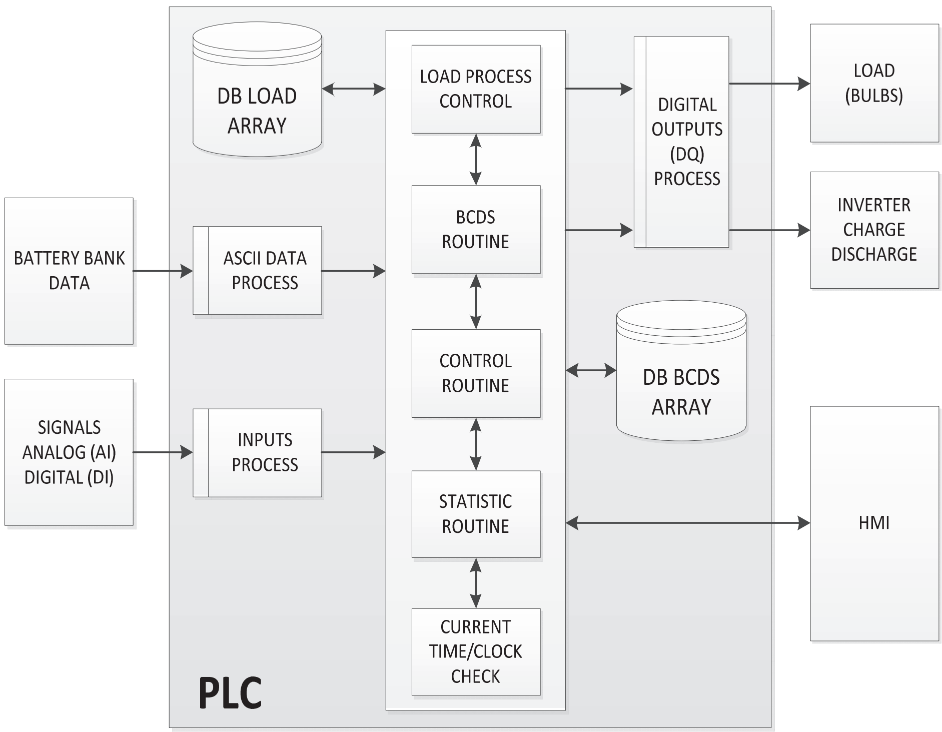

Figure 3.7 Relation of data flow and modules in PLC software

PLC reads input signals, routes them through the input process function. Analog input is the main indication of EMS. It gives feedback of the consumed energy from the grid by measuring current from the grid. Battery data are acquired by the ASCII protocol through serial communication. Control routine is the subprogram in PLC. This routine uses input signals and battery data for load control. Thus it switches load groups on and off according to the current time of the day. HMI application transfers BCDS data to PLC. After BCDS, received PLC starts to control inverter modes by using the BCDS routine function on the electrical level through digital outputs. It keeps the system within safety limits. Temporary and retain data are being stored in data blocks (DB). These data blocks are the DB load array and DB BCDS array. Furthermore, all main parameters of the system are saved by a statistic routine procedure. It is designed to have access to PLC data from HMI at any moment of time.

3.2.3 PC software – "PriceGrabber"

The main software programs developed in EMS consist of two applications. The first is "PriceGrabber" written in C# language. It uses Internet protocols to make requests for day-ahead prices from Elering TSO website every day at midnight. The application writes prices as an array to the text file, which might be processed later on. The code list of the PriceGrabber program is presented in Appendix 1.

The C# language was selected for programming because of a wide selection of functions for the analysis of statistic (prices history) and for its large processing power. C# is a well-known programming language encompassing strong typing, imperative, declarative, functional, generic, object-oriented (class-based), and component-oriented programming disciplines [75]. C# is also powerful, type-safe, and object-oriented. Developed by Microsoft within its .NET initiative, later it was approved as a standard by European Computer Manufacturers Association (ECMA-334) and ISO (ISO/IEC 23270:2006). C# is one of the programming languages intended for the Common Language Infrastructure [75].

Figure 3.8 illustrates the main data flow and the principle of work of PriceGrabber software. HMI executes PriceGrabber and it creates connection to the Internet and fetches unformatted price data by subfunctions on initialization.

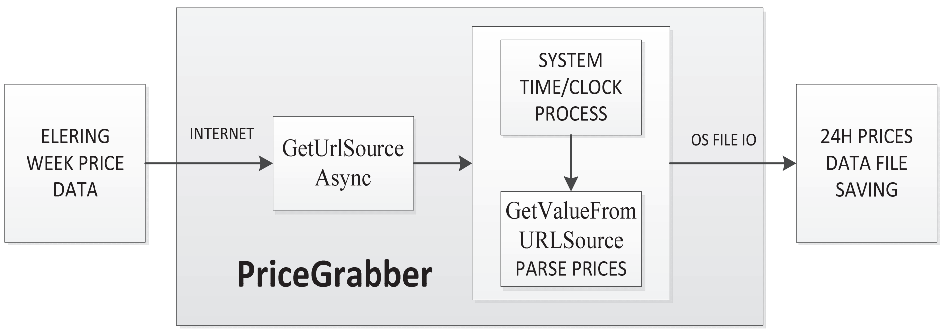

Figure 3.8 PriceGrabber service instance in PC (C# EMS application)

Figure 3.9 shows the procedure of the main function "GetUrlSourceAsync" and other functions in detail. Unformatted price data consist of values for the entire week, thus PriceGrabber takes system date and time to find out values valid only for the current day. With the help of the function "GetValueFromURLSource" software parses price values and saves them into the text file. Later on, HMI processes these data from the file and uses for BCDS creation.

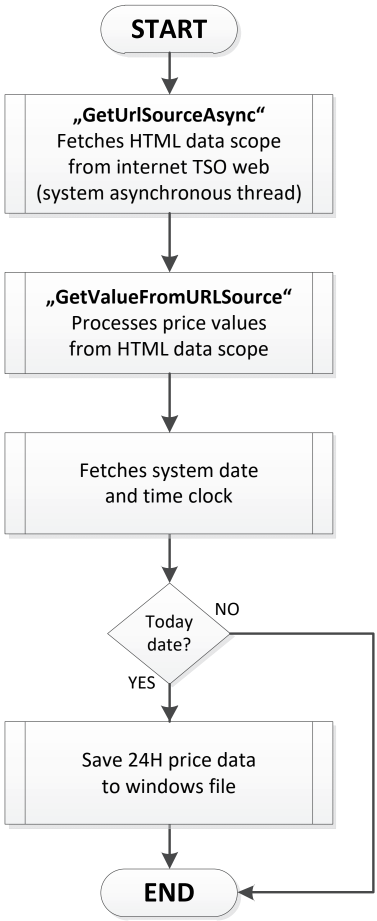

Figure 3.9 Data flow logic and the principle of work of PriceGrabber software

3.2.4 Design of HMI software (Graphical User Interface control application with common workflow guideline)

The second and the main software part of EMS PC is the HMI visualization application. The HMI has been created to provide GUI for end customer. HMI also contains required options for testing purposes of mathematical models and algorithms. This software was programmed in the Siemens development environment TIA WinCC V13 Advanced, which is a powerful system to create the project of Supervisory Control and Data Acquisition (SCADA) [76] types in PC systems. This environment includes features for visualization, reporting and logging; user administration and flexibility with VB scripts; customer-specific ActiveX Controls. It can be included into automation solutions based on the

Transmission Control Protocol and the Internet Protocol (TCP/IP) Ethernet networks [77]. Ethernet connection in EMS is used to transfer data between the PLC and the HMI. Basically, HMI is the main part of EMS software that has different tasks [V]:

- to acquire battery data from PLC (V, I, SOC tags) and archive them to the Structured Query Language (SQL) database; the system updates tag values every second and saves their mean values to the database every 30 seconds;
- to monitor battery data and all other main data;
- to control load groups in the manual mode; for this purpose, it has graphical elements, like buttons and switches;
- to acquire price data from the source file prepared by PriceGrabber;
- to process load and price data according to special algorithms and to create BCDS;
- to transfer BCDS into the PLC;
- to synchronize the date and time between HMI and PLC.

The algorithm used inside HMI attempts to find out the best (which means more profitable for end customer) BCDS for the BESS [VI]. It has been developed and upgraded twice during this thesis research and it is described in more detail in the previous chapter. Currently, EMS works on the basis of DAA. HMI visualization design has all required GUI for EMS control. Figure 3.10 shows the topology of HMI screens.

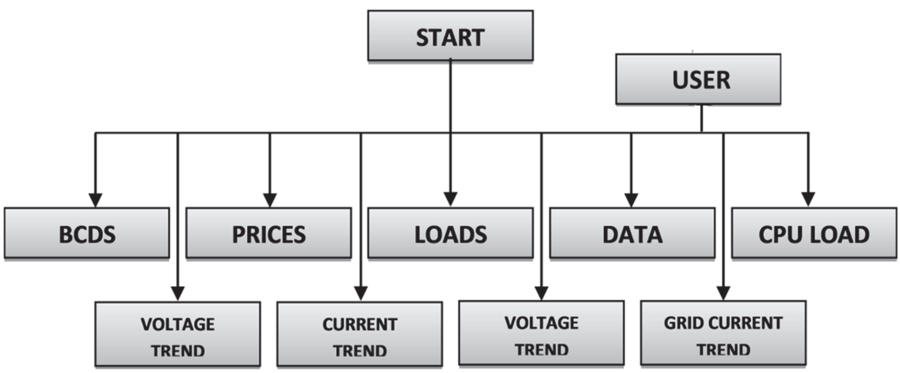

Figure 3.10 Topology of HMI visualization screens

HMI screen structure has a simple scheme; on the other hand, it provides all necessary parts of EMS control and monitoring. The main screen of the visualization application is shown in Figure 3.11.

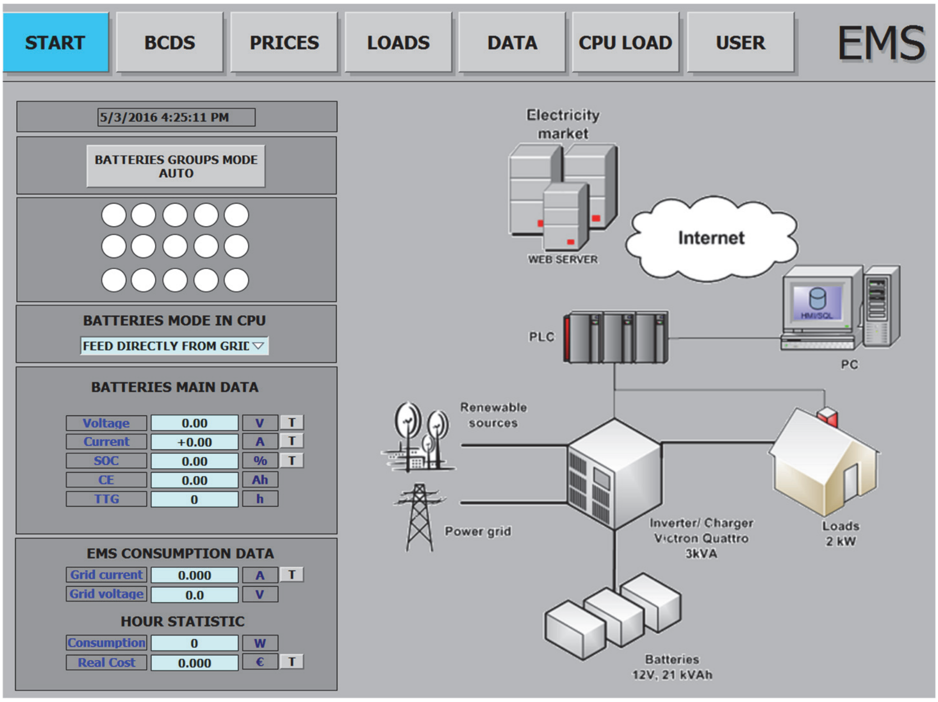

Figure 3.11 HMI main start screen

Basically, EMS is designed for permanent work, which means it can be used in a household consumption system like any other appliance for years. Occasionally, only BESS requires some maintenance, nonetheless the PU inverter has been built to provide this maintenance automatically when needed. Thus, a brief checklist from the guidelines to provide complete automatic independent work of EMS should consist of the following:

- EMS system completely powered up;
- PU unit fed by grid connection;
- Server PC switched on, having Internet access;
- PC and PU interconnected by the Ethernet network;
- work mode of EMS set to automatic, i.e. HMI acquires data from electricity market and creates BCDS for the entire system;
- PLC controls load groups and BESS according to BCDS.

Automatic mode should be set in HMI with the special switch either on screen “Prices” or screen “BCDS”, as shown in Figure 3.12; furthermore, power switch of Victron Energy inverter has to be in position “ON”.

Taking into account that HMI processes new day-ahead prices at 00:00 EET [V], the new BCDS is generated almost at the same moment and is valid until the next day and the next calculation of BCDS.

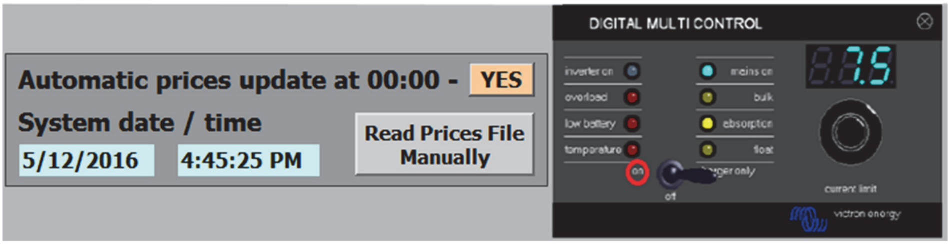

Figure 3.12 States of EMS switches for automatic work of the system

Figure 3.13 shows an example of the generated BCDS according to DAA. BCDS array consists of 24 bytes, each at the value from 0 to 2, standing for modes of BESS accordingly: Idle – BESS is not involved in energy management and the load is fed directly from the grid; Discharging – load consumption is completely fed by battery energy, no power from the grid; Charging – load consumption is fed by the grid, batteries are charging from the grid. A consumer is able to check and edit the BCDS array any time during a current day from screen “BCDS”. In order to change the mode of BESS for any particular hour, a new value has to be entered into the BCDS field of that hour.

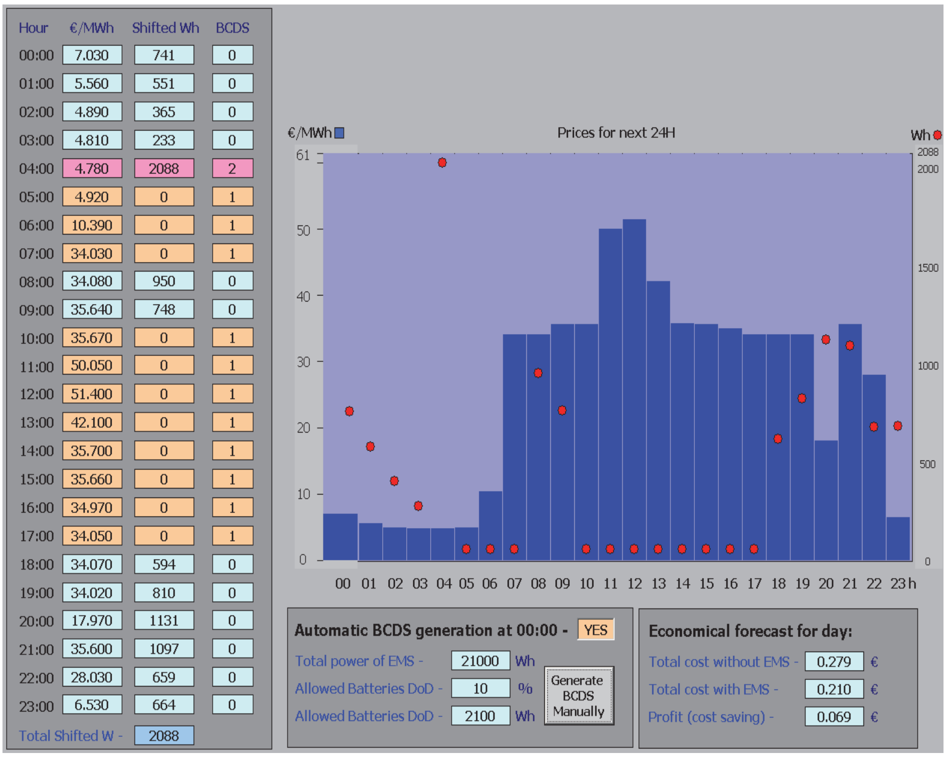

Figure 3.13 HMI BCDS screen

For instance, some hours were set to charging and idle states manually in Figure 3.13. Another option to switch over load groups and BESS modes is with the help of special control elements in HMI. Figure 3.14 illustrates manual control buttons for load groups and Figure 3.15 shows the manual selector for BESS modes.

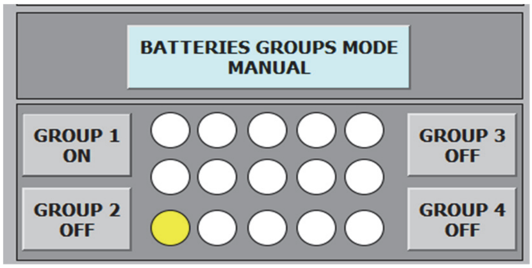

Figure 3.14 Manual switching of load groups

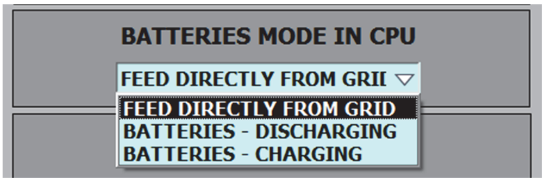

Figure 3.15 Manual selection of each BESS mode

To conclude this chapter, a new EMS was developed for testing of the participation in the open electricity market. EMS design in terms of power and energy capacity is close to the demand of a real household. Hardware and software subsystems were compiled for EMS. The HMI consists of the control algorithm DAA described in Chapter 2.

4. ECONOMICAL EVALUATION AND VERIFICATION OF EMS

4.1 Economical evaluation and required electricity price difference

The developed and designed EMS with DAA was practically tested in the laboratory of Tallinn University of Technology for a one-week period. Since one day or 24 hours is not very informative to measure the DAA rate, the week time period was taken to calculate an average day feasibility of the algorithm [78]. Comparative results of DAA and cost of energy without EMS during the time period of 11.11.14 – 17.11.14 are shown in Table 4.1 and Figure 4.1.

Table 4.1 Energy cost with and without DAA

Date	**Result**		
	No EMS, cost (¢)	***DAA, cost (¢)***	***Profit, %***
11.11.14	35.31	23.28	34.06
12.11.14	37.16	30.32	18.41
13.11.14	41.57	31.49	24.24
14.11.14	44.10	32.31	26.73
15.11.14	50.07	49.68	0.79
16.11.14	48.61	46.77	3.79
17.11.14	40.78	29.66	27.29
Total	297.60	243.50	
Day's average	42.51	34.79	18.18
Day's profit (*DayP)*	0.00	7.73	

One week period may not give exact statistics, but can lead to some conclusions. Day-ahead prices are changing every day, thus consumption even with constant load pattern results in different costs for different days. Monday cost was the smallest - only 35 ¢ and Friday cost was the highest – 50 ¢. Depending on the dispersion of the prices for day-ahead range, the algorithm also achieves different results for each particular day. For example, Monday gave a profit by using of EMS in 34% and Friday only around 1%. An average day profit of EMS as compared to household without EMS gave 18%.

The day profit result obtained with DAA is 7.73 ¢, which was very close to average theoretical result of 7.33 ¢ for the time period 2014-2015. Despite the fact that RTPA was tested only theoretically, it can be assumed that a practical result will show the same accurate result like DAA. This means that the difference between the results of algorithms will be the same in 3 percent points. The beneficial saving of DAA usage as compared to costs of energy for household consumption without BESS is 18.1% per day. Thus, price swing growth during the day increases the profit of both algorithms [79]. This has to be taken into account since the price of open electricity market will increase if energy grid taxes and fees (based on the amount of energy consumption) of local TSO are considered. Figure 4.2 illustrates total electricity cost for end consumer in Estonia according to 2015 [80]. It is clear from that observation that electricity cost increases three times for end customer in relation to raw market price. Consequently, the possible feasibility of the EMS system could grow three times higher, and can be assumed as follows: 0.23 € for DAA and 0.18 € for RTPA per one working day of EMS. To find if the participating on the open electricity market is feasible or not with use of EMS, the total cost and investment of the system has to be revised.

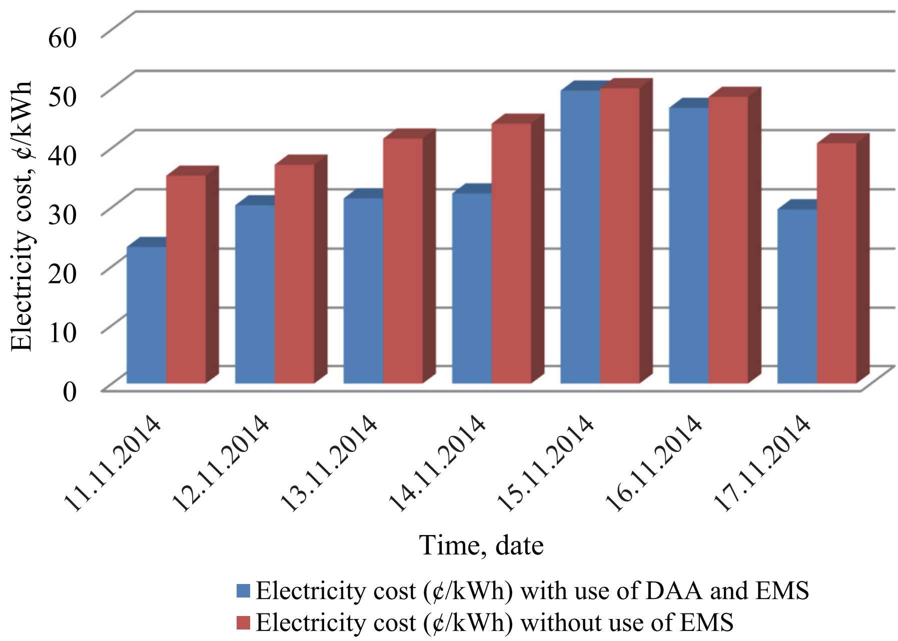

Figure 4.1 Everyday electricity cost for a customer with and without the use of EMS

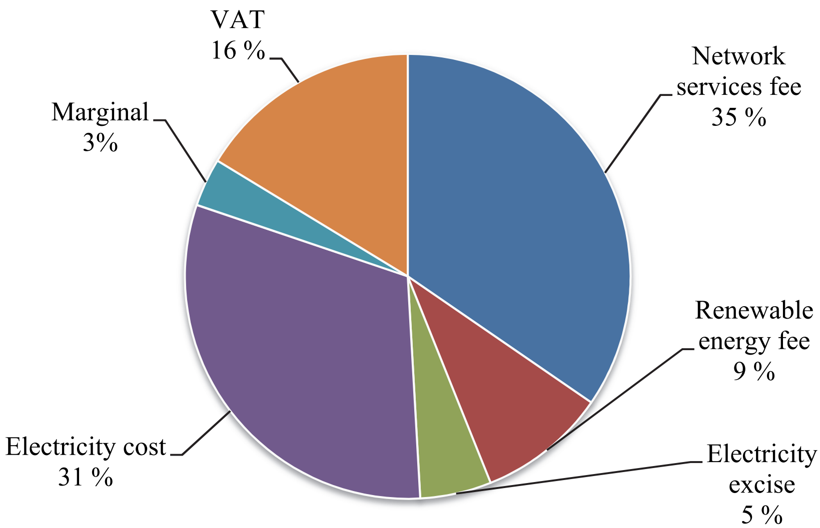

Figure 4.2 Components of the total cost of electricity in Estonia in 2015 [80]

Based on the considerations in Chapter 1, it may be confirmed that the main part of EMS is the battery bank. The cost of components in the pilot EMS as compared to the total cost of EMS = 5200 € (EMS_{total}) [VI] is as follows:

- batteries 50%;
- inverter with power devices 35%;
- PC with control devices 15%.

Thus, it is obvious that battery bank composes the largest part of EMS_{total} and its limited lifecycle [81], it also influences investment return possibilities. Taking into account the decreased system DoD of 14% and increased amount of cycles of the AGM batteries, the required day profit $DayP_r$ is calculated from (4.1):

$$DayP_r = \frac{EMS_{total}}{Cycles} = \frac{5200}{4000} = 1.3€ = 130¢ . \quad (4.1)$$

Furthermore, required 1 kWh of average electricity market price difference *Fr* could be calculated from (4.2):

$$Fr = \frac{EMS_{total}}{Cycles \cdot E_{DoD}} = \frac{5200€}{4000 \cdot 3kWh} = 0.433 \frac{€}{kWh} . \quad (4.2)$$

This price difference 0.433 €/kWh or 433 €/MWh is required between minimum and maximum price on market in terms of ideal (without losses) charge – discharge cycle of battery. The day profit equal or greater than 130 ¢ can be achieved also with a higher swing of minimum and maximum prices. Required swing can be calculated for DAA and should respond to the system of inequation (4.3):

$$\begin{cases} DayP \geq 130 \\ DayP = C_{tot} - C_{DAA} \\ C_{tot} - C_{DAA} \geq 130 \end{cases}. \tag{4.3}$$

Equating of C_{tot} and C_{DAA} with their members is shown in (4.4) and (4.5):

$$C_{DAA} = z\sum_{i=0}^{m}\left(P_{load}(t(i)) \cdot Fp(t(i))\right) + \sum_{d=m+1}^{22}\left(P_{load}(t(d)) \cdot Fp(t(d))\right) + P_{load}(t(23)) \cdot Fp(t(23), \tag{4.4}$$

$$C_{tot} = \sum_{i=0}^{m}\left(P_{load}(t(i)) \cdot Fp(t(i))\right) \cdot x_2 + \sum_{d=m+1}^{22}\left(P_{load}(t(d)) \cdot Fp(t(d))\right) + \left(P_C \cdot Fp(t(23))\right) \cdot x_1, \tag{4.5}$$

where z coefficient - a variable used to find out the difference between the minimum average price and the shifted cost of energy with maximum prices. Both equations of costs have the same parts for idle hours, after eliminating these, the inequation is expressed by (4.6):

$$\begin{gathered} \left(z\sum_{i=0}^{m}\left(P_{load}(t(i)) \cdot Fp(t(i))\right) + P_{load}(t(23)) \cdot Fp(t(23))\right) - \\ \left(\sum_{i=0}^{m}\left(P_{load}(t(i)) \cdot Fp(t(i))\right) \cdot x_2 + \left(P_C \cdot Fp(t(23))\right) \cdot x_1\right) \geq 130 \end{gathered}. \tag{4.6}$$

According to the two-year price statistics of 2014-2015, the average minimum price *Fp*(t(23)) is 2.2 ¢ and the average load at an hour with minimum price P_{load}(t(23)) is 0.4 kWh. The average cost of 3 kWh shifted from most expensive hours and used from battery latter is 12 ¢. Assuming that this cost has a major effect on *DayP* value, it is possible to calculate the difference of the cost necessary to match the required value in 130 ¢.With mode variables $x_2 = 0$ and $x_1 = 1$ and average values, the inequation is expressed in (4.7):

$$\left(12z + 0.4 \cdot 2.2\right) - \left(0 + 3 \cdot 2.2 \cdot 1\right) \geq 130, \tag{4.7}$$

after linear transformation, z coefficient is found from (4.8):

$$z \geq \frac{130 - 0{,}88 + 6{,}6}{12} \geq 11.31 \tag{4.8}$$

and the required day profit for the investment return can be achieved if the total cost of energy at maximum price hours will grow by 11.31 times. At the same time, the minimum average price will stay at 2.2 ¢.

Today's price swing on the market is not too high and simple calculations show that currently it is impossible to return the total cost of the EMS in its lifetime neither with day profit DAA result 0.23 € nor with day profit RTPA result 0.18 € [VI] [VII].

4.2 Comparison of 1 kWh price for different battery types

Despite good technical parameters of AGM, today's Li-ion prices offer much better opportunities while price trend forecasts are still better. It is possible that cost of Li-ion batteries in electric vehicles will drop dramatically by 2020, whereas Tesla's "Gigafactory" may make great impact and contribution to achieve that. The electric car market, in turn, is making large-format batteries cheaper for grid use [81]. For that reason, it is required to discuss the use of the Li-ion factor for the EMS project.

As compared to lead acid, Li-ion batteries are a relatively new invention as they have been used commercially since the 1990s. Lithium technology has become well proven and understood for powering small electronics like laptops or cordless tools and has become increasingly common in these applications – edging out the older NiCad (Nickel-Cadmium) rechargeable battery chemistry due to many advantages of lithium. Along with Li-ion batteries, LiFePO4 type of batteries holds a good position. In 1996, a new formula for mixing lithium ion batteries was developed – Lithium Iron Phosphate. Known as LiFePO4 or LFP, these batteries have a slightly lower energy density but are intrinsically non-combustible, and thus much safer than Lithium-Cobalt-Oxide (LCO) [82].

Lithium Nickel Manganese Cobalt Oxide (NMC) is one of the most successful Li-ion systems. Similar to Li-manganese, these systems can be tailored to serve as Energy Cells or Power Cells. For example, NMC in an 18650 cell for moderate load condition has a capacity of about 2,800 mAh and can deliver 4 A to 5 A; NMC in the same cell optimized for specific power has a capacity of only about 2,000 mWh but delivers a continuous discharge current of 20 A. A silicon-based anode will go to 4,000 mAh and higher but at reduced loading capability and shorter cycle life. Silicon added to graphite has the drawback that the anode grows and shrinks with charge and discharge, making the cell mechanically unstable. Once the advantages are considered, Lithium-Ion batteries become exceedingly tempting [83].

To find a probable advantage of another type of battery as compared to AGM in EMS, the data from [84] were used. The main values can be found in Table 4.2. All costs of batteries are increased by the costs of EMS components amounting to 2340 €. Since the number of cycles available only with DoD equals or is greater than 30% in data sheet, the maximum total capacity of battery bank is considered as 10 kWh. The most adequate rate parameter could be the price of 1 kWh in relation to the total cost of EMS.

Table 4.2 Electricity cost of 1 kWh (valid for November 2016) related to the total EMS cost with reduced total capacity of battery bank [84]

	Depht of Discharge	Max no. of cycles	required total capacity to use 3 kWh	investment costs € batteries	total investment costs € to EMS	costs € for each kWh
LiFePo4 PYLONTECH	48%	9800	6.25	4000	6340	0.22
OPzV tubular (GEL)	30%	5600	10	2400	4740	0.28
OPzS tubular (floodes)	30%	5000	10	2200	4540	0.30
Lithium Ion (NMC)	48%	11000	6.25	4375	6715	0.20
AGM Heavy Duty	30%	2000	10	1400	3740	0.62
GEL Heavy Duty	30%	2300	10	2000	4340	0.63
Typ. Lead Acid	30%	1100	10	1200	3540	1.07

At today's prices, the Li-Ion batteries show a better result as compared to Lead Acid and AGM batteries for 1 kWh. However, the required day profit with the best result of Li-Ion NMC is unable to return the investment back. The required day profit in the case of NMC is 0.61 € (4.9):

$$NMC\_DayP_r = \frac{EMS_{total}}{Cycles} = \frac{6715\,€}{11000} = 0.6€\,. \tag{4.9}$$

Thus, required 1 kWh of average electricity market price difference could be calculated from (4.10):

$$NMC\_Fr = \frac{EMS_{total}}{Cycles \cdot E_{DoD}} = \frac{6715€}{11000 \cdot 3kWh} = 0.203\frac{€}{kWh}\,. \tag{4.10}$$

This calculation illustrates that to reach the payback value of cycle cost per day with DoD 3 kWh, the minimum required 1 kWh electricity price has to be 0.203 €/kWh (203 €/MWh). It is higher than average market price, thus it is still almost impossible to build EMS with the current market kWh price. However, if the battery cost continues to decrease, it will lead to the fall of the total cost of EMS. With the certain level of EMS_{total}, the system will become profitable. In this case, EMS_{total} with AGM batteries and DoD of 14% should not be higher than 920 € to match DAA limits in an average day profit of 0.23 € and 4000 cycles of battery life. The EMS_{total} with RTPA should be less than 720 € [VII].

UBS, in a report based around a discussion with Navigant Research, says the 230 $/kWh mark for the BESS will be reached by the broader market within two to three years, and will likely fall to 100 $/kWh. Navigant estimates the cost of materials going into a battery at the Tesla Gigafactory on a processed chemical basis (not the raw ore) is 69 $/kWh. The cost of the battery is only ~10-20%

higher than the bill of materials – suggesting a potential long-term competitive price for lithium-ion batteries could approach ~100 $/kWh. A typical 'load shifting' 4-hour battery (designed to address the afternoon/evening peak) costs anywhere from ~720-2,800 $/kWh, depending entirely on the scale of the lithium-ion battery employed and the size of order. The average 500-700 $/kWh for a typical battery is probably closer to the 2,000-3,000 $/kW when including the balance of the system costs (around 400-500 $/kW), with a trend towards around 1,500 $/kW within the next 3 years [85] [86].

According to optimistic system price 100 $ (94 €) per 1 kWh the total cost of current (21 kWh) EMS is 1974 €, cost of scaled (10.5 kWh) EMS is 987 € and cost of EMS with Lithium Ion NMC (6.25 kWh) battery bank is 588 €. Different day profit values for previously mentioned EMS systems are shown in Table 4.3.

Table 4.3 Time periods for investments return depending on the day profit value and the total cost of the EMS

Required day profit in €	**Different total cost values for EMS in €**				
	5200	3000	1974	987	588
	Investment return time in years				
1.7	8.5	4.9	3.2	1.6	1.0
1.5	9.6	5.6	3.7	1.8	1.1
1.4	10.3	6.0	3.9	2.0	1.2
1.3	11.1	6.4	4.2	2.1	1.3
1.2	12.0	6.9	4.6	2.3	1.4
1.1	13.1	7.6	5.0	2.5	1.5
1.0	14.4	8.3	5.5	2.7	1.6
0.9	16.0	9.3	6.1	3.0	1.8
0.8	18.1	10.4	6.9	3.4	2.0
0.7	20.6	11.9	7.8	3.9	2.3
0.6	24.1	13.9	9.1	4.6	2.7
0.5	28.9	16.7	11.0	5.5	3.3
0.4	36.1	20.8	13.7	6.9	4.1
0.3	48.1	27.8	18.3	9.1	5.4
0.2	72.2	41.7	27.4	13.7	8.2
0.1	144.4	83.3	54.8	27.4	16.3

It should be take into account that commonly the investment return time is limited with maximum lifetime of EMS in 15 years [VI]. According to table 4.3

it follows that current investment (5200 €) into EMS with DAA day profit (0.23 €) or RTPA day profit (0.18 €) cannot be returned during the lifetime of the battery bank. However, it is possible if EMS cost will be reduced to 100 $ per kWh and total cost of system will be less than 1000 €.

It should be also taken into account that the use of EMS provides other benefits such as increased supply reliability, ability to combine an electric system with other renewable energy sources and simpler implementation of the household network into a smart grid, if needed. As was mentioned above, price swing growth during the day on the electricity market or increasing the power of the EMS could be the boost factor for payback during lifetime [87] or penetrating to the EMS renewable energy sources as distributed power generators [88] [89].

5. CONCLUSIONS AND FUTURE WORK

This thesis focuses on the research and development of a storage based energy management system for households on open electricity market, day-ahead electricity prices and real-time prices. The main scientific result of the work is the development of an energy management system for grid connected households and analysis of its feasibility, which includes analysis of most suitable demand side management options for household as follows:

1. load patterns with non-shiftable loads
2. day-ahead and real-time price markets in the Estonian region (NP data)
3. battery type and size of capacity

as well as development of new mathematical models and control algorithms for BESS [V] [VI] [VII]:

1. day-ahead prices based control model for day-ahead electricity market
2. real-time prices based model for intraday electricity market, with a trading time frame in one hour before distribution.

For further research and development of the algorithms described in the thesis, in terms of a practical value, the author proposes a new EMS design with a focus on the following tasks:

1. to design a real electrical cabin with devices required for hardware of the new energy storage integrated energy management system
2. to develop a server PC with new HMI software for the control of the energy management system and fetching data from an energy operator (including server PC with data management and fetching data from an energy operator)
3. to prepare guidelines for energy management system control with an overview of development possibilities

With support of the practical part, the author conducted research and testing of EMS in the laboratory during a one-week period to evaluate the real EMS behavior and obtain main system indicators on the real market data. The main outcomes of the theoretical and practical research are as follows:

- According to all specific constraints and limits of EMS, including economical part, the most reasonable battery type for EMS at developing stage was Lead-Acid, specifically VRLA/AGM type.
- In an average household, the capacity of battery bank to cover household energy demand with non-shiftable load has to be 7 kWh with DoD 100% or 21 kWh with DoD of 30%, which is approximately equal to daily electricity consumption.

- Developed and designed new universal EMS, which can use day-ahead price or stochastic RTP based control.
- DAA and RTPA use price arbitrage algorithms with three modes of BESS work, which is a simpler and advance implementation as compared to complicated industrial systems.
- Practical and theoretical result of DAA use in EMS is around 7% more profitable than the use of electricity without EMS. Theoretical profit of RTPA is around 6%.
- Even reduced DoD of batteries to 14% and increased amount of life cycles up to 4000 still requires a day profit equal to 1.3 € to return investment to EMS. According to algorithms, day profit result, the cost of EMS, should not exceed 920 € in the case of DAA and should not be more than 720 € in the case of RTPA, to return investment to the system during its lifetime.
- Today, the Li-ion battery of type NMC may be more feasible than AMG with a required day profit around 0.6 €.
- Use of EMS with DAA will return investment into the system or bring a profit if the electricity price of hours covered by batteries is 11 times higher than average minimum electricity price (according to years 2014-2015).

The key conclusion is that with today's electricity prices and the total cost of particular EMS, no return investment to EMS is possible; thus, it is not feasible for households and small customers. According to required demand of energy for small systems like an apartment, the components of EMS will run out of service life, before they achieve required profit to cover an investment. On the other hand, it still may be feasible in the near future. Since battery cost in EMS produces 40%-50% from the total price, due to technology development, the continual drop of battery prices is essential for a decrease of EMS total price [VII]. Furthermore, price swing growth during the day on the electricity market or increasing the power of the EMS could be a boost factor for payback during lifetime [VI]. This means either reduction of batteries and EMS component price by 300-400% or an increasing swing of electricity prices by 11-12 times will make EMS feasible for households. Further research into the issues discussed should continue.

Future research areas

The next challenge for the author will be to improve RTPA for more effective price prediction methodologies and an interconnection system to smart grid with renewable sources and an economical use of real-time tariff in the demand-side using available renewable energy sources. Furthermore, the experimental study of power losses and efficiency enhancement methods of the proposed EMS will take place. Energy management systems and smart house systems are developing very fast. New solutions and algorithms are emerging, which can be considered for upgrading the work, even the general operating principle of the EMS, will remain the same.

Another area of interest could be integration of EV and EMS. Today investments in EVs are already significant and create huge opportunities for integration with smart grids. It is a strong argument in support of a feasible use of electric car batteries as an energy reserve in households. EV connected to the grid could help cut electricity demand during peak periods and prove especially helpful in smoothing variations in power generation introduced to the grid by variable renewable resources such as wind and solar power [90].

The battery bank type for EMS has to be revised in the future. Already today, NMC Li-ion battery may be more feasible than AMG and rapidly declining cost of Li-ion battery packs will bring more opportunities to the electric car market, and also for household solutions. Battery banks with larger amounts of used energy are already more competitive to reach this goal due to deeper depth of discharge. It is the case especially if the start price for battery bank is low, due to mass production benefits and damping system like in the case of Tesla's "Gigafactory" and "Powerwall line" banks [91]. This product is able to be cost effective with upgraded EMS algorithms.

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ABSTRACT

Current thesis explores the feasibility of Energy Management System use in households. Open electricity market gives an opportunity to participate in energy trading with different tariffs and time resolutions for even small consumers. Since January 1st, 2013, all participants in Estonia became eligible consumers in the fully open electricity market. Topicality of the study lies in the fact that in a short term, entire households must transfer to the new tariff systems across Europe to purchase electricity from the free market. The main goal is to reduce the cost for consumed electricity by using energy storages and price arbitrage. Use of a battery charge-discharge-schedule and taking advantage of the low price periods by importing more energy and storing it, while reducing the imported power during high price periods by supporting the load with the stored energy. However, consumption characteristics and patterns remain unchanged, providing unchanged comfort limit for end customer. The new real EMS was designed and created within the scope of this thesis. Also, new mathematic models were developed to interact at EMS with different price tariffs like day-ahead and real-time. DAA was tested in the laboratory during one week of EMS work.

Chapter 1 describes the open electricity Nord Pool market and gives an overview of energy storage technologies for demand side management.

Chapter 2 addresses mathematical models for energy shifting with battery energy storage and provides the development of mathematical models for day-ahead price and real-time price control algorithm.

Chapter 3 covers the designed and developed new Energy Management System with guidelines of its usage.

Chapter 4 presents an evaluation of the economical part of the system. Also, the calculation of the needed price swing of electricity is analyzed.

KOKKUVÕTE

Käesolev doktoritöö uurib võimalusi, kuidas kasutada Energy Management Systemi (energia haldamise süsteemi) koduses majapidamises. Alates 1. jaanuarist 2013 on Eestis kõigil tarbijatel võimalus osta elektrienergiat avatud elektrituru tingimustes. Tänu avatud elektrituru tingimustele on ka väikestel elektrienergia tarbijatel võimalik saavutada kokkuhoidu. EMS-i peamine eesmärk on vähendada rahalisi kulutusi tarvitavale elektrienergiale. EMS-i efektiivsus tuleneb madala hinnaga elektrienergia salvestamise arvelt, mida tarbitakse kõrge elektrienergia hinna perioodil. EMS-i juures on kasutatud uusimaid matemaatilisi mudeleid, mis analüüsivad elektrienergia tarbimist ja elektrienergia hindade muutumist eelneval perioodil ning sellele toetudes optimeerib EMS elektrienergia tarbimist reaalajas ning prognoosib optimaalset elektrienergia tarbimist kuni üks ööpäev ette. DAA „Ööpäeva ette hinna algoritmi" on testitud EMS-i töös ühenädalase perioodi jooksul.

Esimene peatükk annab ülevaate avatud elektriturust Nord Pool ja tarbijate vajadusest EMS-i järele.

Teine peatükk kirjeldab matemaatilisi mudeleid, mille abil optimeeritakse madala hinnaga elektrienergia salvestamist ja salvestatud elektrienergia tarbimist reaalajas, ning prognoosib optimaalset elektrienergia tarbimist kuni üks ööpäev ette.

Kolmas peatükk annab ülevaate uuest EMS-ist ja arutleb selle kasutamisvõimaluste üle tulevikus.

Neljas peatükk analüüsib süsteemi majanduslikku efektiivsust ja vajalikku hinnavahet süsteemi tasuvuseks.

ELULOOKIRJELDUS

1. Isikuandmed

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Tallinna Tehnikaülikool	2008	Elektriajamid ja jõuelektroonika/ bakalaureusekraad
Tallinna Tööstushariduskeskus	2003	Mehhatroonika/kutseharidus
Pärnu Vene Gümnaasium	2000	Keskharidus

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

Keel	Tase
Vene keel	Emakeel
Eesti keel	Kõrgtase
Inglise keel	Kesktase

5. Täiendusõpe

Õppimise aeg	Täiendusõppe läbiviija nimetus
2012	Simatic TIA Portal Programming 1 (TIA-PRO1), Nürnberg, Saksamaa
2013	Programming of safety related SIMATIC S7 controller via Distributed Safety

6. Teenistuskäik

Töötamise aeg	Tööandja nimetus	Ametikoht
2009-	Saksa Automaatika OÜ	Tarkvara insener
2007-2009	Siemens AS	Programmeerija
2007	ABB Automation Gmbh	Projekteerija (praktika)
2006	ELSA AS	Elektrimontöör
2004-2005	Merevägi MJ Sulev	Vanemelektrik
2003-2004	Pärnu Soojus AS	Elektrik
2002	Coca-Cola AS	Liini operator

7. Teadustegevus
Projekt SF0140016s11 Aktiivsete elektrijaotusvõrkude muundurite topoloogiad ja juhtimismeetodid

8. Kaitstud lõputööd
Magistritöö: SCA katlamaja automaatjuhtimise ja talitlusjärelevalve väljatöötamine, 2010 juhendajad vanemteadur Argo Rosin, Tallinna Tehnikaülikool

9. Teadustöö põhisuunad
Energiasalvestid, Reaalajatariif, tarkvõrgud, SMART

CURRICULUM VITAE

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3. Education

Educational institution	Graduation year	Education (field of study/degree)
Tallinn University of Technology	2010	Electrical drives and Power Electronics/ MSc
Tallinn University of Technology	2008	Electrical drives and Power Electronics/ BSc
Tallinn Industrial Education Centre	2003	Mechatronics / Vocational Education
Pärnu Russian Gymnasium	2000	Secondary Education

4. Language competence/skills (fluent; average, basic skills)

Language	Level
Russian	Mother tongue
Estonian	Fluent
English	Average

5. Special Courses

Period	Educational or other organization
2012	Simatic TIA Portal Programming 1 (TIA-PRO1), Nürnberg, Germany
2013	Programming of safety related SIMATIC S7 controller via Distributed Safety

6. Professional Employment

Period	Organization	Position
2009-	Saksa Automaatika OÜ	Software engineer
2007-2009	Siemens AS	Programmer
2007	ABB Automation Gmbh	Designer (trainee)
2006	ELSA AS	Construction electrician
2004-2005	NAVY, Ship Sulev	Chief electrician
2003-2004	Pärnu Soojus AS	Electrician
2002	Coca-Cola AS	Line operator

7. Scientific work
Project SF0140016s11
New Converter Topologies and Control Methods for Electronic Power Distribution Networks

8. Defended theses
MSc: Development of SCA Boiler house Control and Supervision System, 2010 Supervisors Senior Researcher Argo Rosin, Tallinn University of Technology

9. Main areas of scientific work/Current research topics
Energy storages, Real-time tariff, distributed generation, SMART grids

APPENDIX 1. PROGRAM LISTING „PriceGrabber“

```
using System;
using System.Collections.Generic;
using System.Linq;
using System.Text;
using System.Threading.Tasks;
using System.Net;

namespace PriceGrabber
{
    class Program
    {
        // Start of console appplication service
        static void Main(string[] args)
        {
            string source = "";
            List<double> Prices24H = new List<double>();

            // Function call to get HTML data scope
            source = GetUrlSourceAsync();

            // Fetching system date time
            DateTime dt = DateTime.Now.Date;
            string dts = dt.ToShortDateString().Replace('.', '-');
            string target = dts;

            // Loop process of current date price data
            for (int i = 0; i < 24; i++)
            {
                string tar = target + " " + i.ToString().PadLeft(2,
                    '0');
                double prc = 0;

                // Parsing price data from HTML data
                string res = GetValueFromURLSource(source, tar);
                try
                {
                    prc = Convert.ToDouble(res) / 100;
                }
                catch
                {
                }
                if (prc != 0.0)

                // Creation of price array and output it to the
                    screen
                {
                    Prices24H.Add(prc);
```

```
                    Console.WriteLine(prc.ToString());
                }
            }
            // End of service instance
        }

        // Asynchronous fetching HTML data from internet
        static async Task<string> GetUrlSourceAsync()
        {
            string source = string.Empty;
              source = await new
HttpClient().GetStringAsync("http://elering.ee/nps-
       hinnad/?=table");
            return source;
        }

        // Parsing algorithm to filter HTML tags and remove required
price data
        static string GetValueFromURLSource(string source, string
              target)
        {
            int StartPos = source.IndexOf(target);
            if (StartPos >= 0)
            {
                int RealPos = source.IndexOf("left;", StartPos);
                string Cutted = source.Substring(RealPos + 7, 7);
                Cutted = Cutted.Trim(new Char[] { '/', '\\' });
                Cutted = Cutted.Replace('’', ',');
                return Cutted;
            }
            else return "";
        }
    }
}
```

APPENDIX 2. COPIES OF PUBLICATIONS

Paper III

Rosin, A.; Auväärt, A.; **Lebedev, D.** (2012). Analysis of operation times and electrical storage dimensioning for energy consumption shifting and balancing in residential areas. Electronics and Electrical Engineering, 4 (120), 15 – 20.

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2012. No. 4(120)

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ELEKTROS INŽINERIJA

Analysis of Operation Times and Electrical Storage Dimensioning for Energy Consumption Shifting and Balancing in Residential Areas

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Introduction

According to a report by the U.S. Department of Energy in 2008 [1], 74% of the nation's electricity consumption occurs in buildings. This represents 39% of the total energy consumption among all sectors. There are two general approaches for energy consumption management in buildings: reducing consumption and shifting consumption [2]. The former can be done through raising awareness among subscribers for more careful consumption patterns as well as constructing more energy efficient buildings [3].

In the household without energy generation units, the main cost reducing possibilities are shifting of loads and/or replacing the less efficient loads with more efficient ones. Profitability of load replacing depends on energy costs, consumption amount, investments (replacement costs), exploitation costs and lifetime of the device. The shifting profitability depends on load priorities and storage possibilities. The household consumption is not a homogenous group, different appliances have different regimes, priorities and roles [4]. P. Kadar has divided household electrical appliances to three groups: critical load, flexible load, and autonomous flexible intelligent load.

Energy storage systems play a key role in shifting critical (not shiftable) loads. Storages can be classified into heating and electrical ones. Heating energy storages are water or space heaters in residential buildings with electrical heating loads. Compared to total consumption, these loads have mainly high energy consumption, which is about 30%...50%. Energy consumption shifting and balancing with existing heating energy storage systems needs small investments, and their profitability is mostly less than one year.

Optimization of electrical energy storage capacitance, control models (including the charging/discharging cycles) are important research questions. The main objectives of customers are:

- To minimize their energy costs;
- To increse the power quality and comfort.

The main objectives of the following analysis are the analysis of operation times and electrical storage dimensioning for energy consumption:

- Shifting, depending on the two-tariff system price and on the Nord Pool Spot price;
- Balancing with and without water heater shifting.

Operation times of home appliances

The following analysis is based on four-week measurements (in February/March 2010). The object of the analysis was a 3-room (67.4 m2) apartment with four habitants (2 adults, 2 children). The object built in 2005 has a two-tariff energy measurement system. The high tariff period in the winter time is from 7 to 11 o'clock (in the summer time from 8 to 24 o'clock) on workdays. The rest is a low-tariff period, including the weekend. For energy consumption measurements 12 *Voltcraft Energy Logger 4000* devices were used. The total measurement error was less than 5% compared with the main energy meter. The total energy consumption by load is shown in Fig. 1.

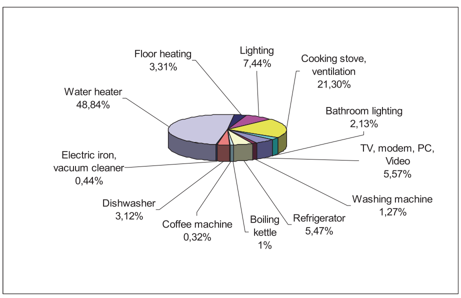

Fig. 1. Energy consumption of loads

By shift-ability, loads can be divided into three priority groups:

I (not shiftable) – cooking stoves, kitchen ventilation, coffee machines (without thermos), bathroom lighting and ventilation, TV sets, PCs with modem, home cinema and audio systems, and local lighting;

II (almost shiftable) – lighting, refrigerators, boiling kettles, coffee machines (with thermos), vacuum cleaners, electric irons, and floor heating for drying purposes;

III (shiftable) – water heaters, washing machines, dishwashers, and floor heating for heating purposes.

Based on the analysis of electricity consumption, the average workday consumption per hour is 0.9 kWh, and the average holiday consumption per hour is 1.4 kWh. Before the consumption shifting and reducing in the workday the average high-tariff consumption is 1.05 kWh/h and average low-tariff is 0.55 kWh/h. There are three peak hours for energy consumption [5]:

- The morning on the workday (from 7 to 8);
- The midday on the holiday (from 12 to 14);
- The evening on the workday or holiday (from 19 to 21).

Main loads which affect the local extremums are: in the morning – water heater; in the midday – water heater and cooking stove; in the evening – water heater, cooking stove and lighting.

Before the consumption shifting and reducing the average ON time period is 4 hours and 36 minutes. The average ON time in the high-tariff period is 2 hours and 10 minutes.

The operation times of home appliances can be divided into three groups:

- Long operation period (3 hours and more): refrigerator, TV, modem, PC, video, lighting, water heater, floor heating;
- Average operation period (between 1 to 3 hours): bathroom lighting, cooking stove & ventilation, iron, vacuum cleaner, dishwasher;
- Short operation period (up to 1 hour): washing machine, coffee machine, boiling kettle, toaster.

Appliances with a long operation period like water heaters, floor heating and refrigerators have an energy storage capability (Table 1). Energy consumption scheduling of about 200-liter water heater and floor heating energy up to six hours does not affect the customers comfort. Control for scheduling of a small water heater (up to 50 liters) and a refrigerator must be reasonable and take into consideration vacancy of the apartment. Water heaters and refrigerators are rarely used on workdays between 9 and 15 o'clock, which makes it possible to shift small water heaters and refrigerators electricity consumption for one to three hours.

Table 1. Operation times and energy consumption of home appliances

Load name(s)	ON-time per day	ON-time/day, %	ON time in high-tariff period	ON time in low-tariff period	Max continuous ON time	Total consumption by loads, %	High tariff consumption, %
Refrigerator	15 h 36 min	65	7 h 24 min	8 h 11 min	17 h 30 min	5.5	47.50
TV, modem, PC, Video	12 h 42 min	53	7 h 5 min	5 h 37 min	16 h	5.6	55.76
Lighting	7 h 58 min	33	4 h 40 min	3 h 17 min	8 h	7.4	58.68
Water heater	5 h 46 min	24	2 h 52 min	2 h 54 min	5 h 30 min	48.7	49.66
Floor heating	4 h 5 min	17	1 h 10 min	2 h 54 min	15 h 30 min	3.3	28.79
Bathroom lighting	2 h 57 min	12	1 h 31 min	1 h 26 min	5 h	2.1	51.35
Cooking stove, ventilation	2 h 12 min	9	1 h 8 min	1 h 4 min	3 h	21.3	51.35
Iron, vacuum cleaner	2 h 2 min	8	0 h 11 min	1 h 50 min	50 min	0.4	9.41
Dishwasher	1 h 7 min	5	0 h 2 min	1 h 4 min	1 h 45 min	3.1	4.36
Washing machine	32 min	2	0 h 0 min	0 h 32 min	1 h	1.3	0.28
Coffee machine	10 min	0,7	0 h 1 min	0 h 8 min	1 h	0.3	12.49
Boiling kettle	7 min	0,55	0 h 4 min	0 h 3 min	7 min	1	61.96

Energy storage dimensioning for consumption shifting in a two-tariff system

If the consumption of all freely shiftable loads (water heater, dishwasher, washing machine) is shifted to the low-tariff period and lighting bulbs are replaced with economy bulbs, the 6.5...7 kWh of almost- and not-shiftable energy consumption stays in the high-tariff period. After consumption scheduling and using of saving bulbs (compact fluorescent lamp) the average high-tariff energy consumption is 0.43 kWh/h.

Fig. 2 shows that at the high-tariff period two high and low consumption periods with a difference of about 7.4 times can be identified. The low energy consumption period is between 7...17 and 21...23 o'clock - with the average energy consumption of 0.165 kWh/h. The high energy consumption period is between 17...21 with the average energy consumption of 1.22 kWh/h.

Two different choices are available for electrical energy storage calculation. First, storage should store energy for the whole high-tariff period. Using a simplified formula (1), storage capacitance of about 6.9 kWh can be calculated

$$E_{st} = E_{hb} - E_{sh} = E_{ha}\,, \qquad (1)$$

where E_{st} – minimum electrical storage capacitance, E_{hb} – high-tariff consumption before shifting of shiftable loads, E_{sh} - shifted energy (energy consumption of shiftables loads), E_{ha} – high-tariff consumption after energy consumption shifting of shiftable loads.

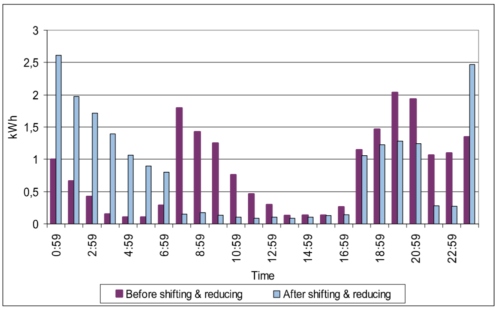

Fig. 2. Electricity consumption before and after load scheduling and power reducing on workdays

Naturally it is important to take into consideration also all energy losses in the scheduling process and system self-consumption.

Second, the storage should store only energy of the high energy consumption period, which means a storage capacitance of about 4.9kWh (about 29% less than described before). In both cases the peak power of the storage system should be approximately between 1.2 and 1.5 kW.

Storage dimensioning for consumption scheduling based on the Nord Pool Spot (NPS) average daily price

Energy consumption in households in the UK is reported in [6] and in Estonia in [7]. Peak hours for UK households are from 06-08 and 13-18. Main peak hours for Estonian average households are at 7-8 and 19-21 on workdays and 12-14 and 19-21 at weekends. It is quite easy to see the possible use of energy storage to smoothen the loads at morning or midday use and even the evening use at weekends. However, some exact calculations are needed in terms of the possibilities to conserve energy at low price before evening peak hours on workdays.

Average NPS price during the measured period in the Estonia (EE) area is calculated as 44.50€/MWh. The NPS price curve is not similar on workdays and at weekends. The maximum price on workdays is 65.93€/MWh and the minimum is 33.35€/MWh. At weekends the maximum and minimum prices are 43.05€/MWh and 29.76€/MWh, respectively. Average price below the EE area average (44.50€/MWh) is 38.02€/MWh (-14.55%) on workdays and 38.26€/MWh (-14.03%) at weekends. Average price above the EE area average is 53.50 €/MWh (20.22%) on workdays and does not exceed the average at weekends.

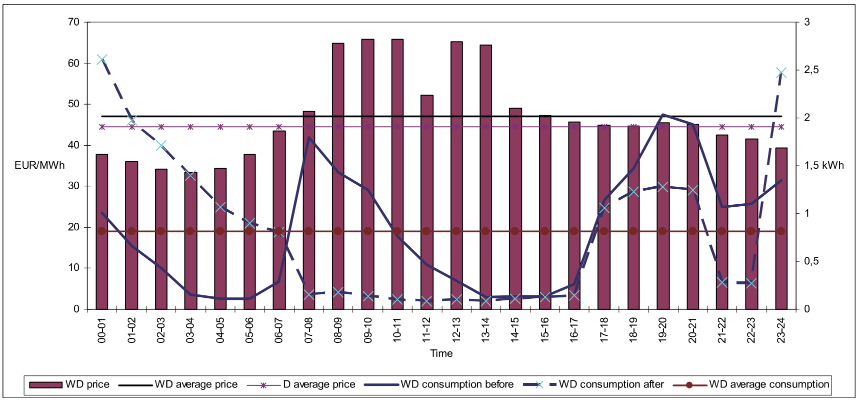

Fig. 3. Average workday price fluctuation compared to electricity consumption before and after scheduling of shiftable loads

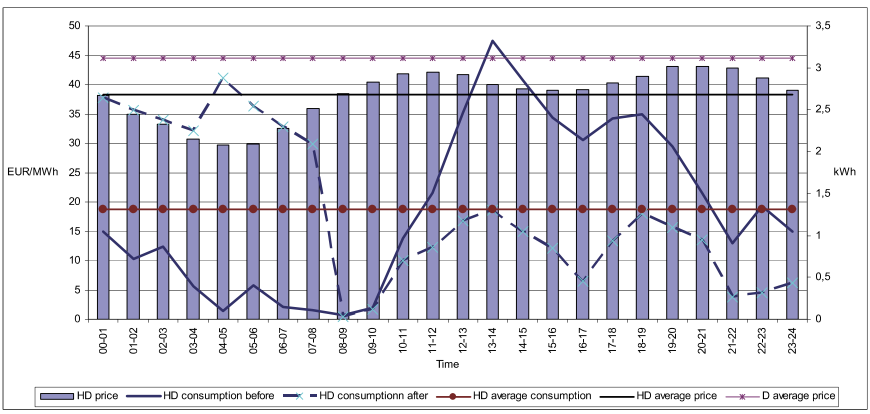

Fig. 4. Average holiday price fluctuation compared to electricity consumption before and after scheduling of shiftable loads

If all shiftable loads on workday (WD) are "switched on" under average price, then at least 1.1 kWh storage system is needed for shifting of energy consumption (Fig. 3).

If all shiftable loads on holiday (HD) are "switched on" under average price, then at least 11.8 kWh of energy consumption should be supplied from the storage system (Fig. 4). If an average price deviation is allowed (43.05 - 29.76)*10% = 1.33€ (10 % from maximum and minimum price difference), then 4.83 kWh should be supplied from the electrical energy storage.

Storage dimensioning for consumption balancing

In the following analysis the consumption of a water heater, dishwasher and washing machine will be shifted with the electrical energy storage system.

To balance electricity consumption it is important to define average electricity consumption and deviation of electricity consumption. The simplified formulas (2) and (3) for the calculation of maximum over- and under-consumption amounts are described as follows:

$$E_i > \overline{E} \Rightarrow \begin{cases} E_{u,\Sigma} = 0, \\ E_{o,\Sigma} = \sum_{i=1}^{n} (E_i - \overline{E}), \\ E_{o,\max} < E_{o,\Sigma} \Rightarrow E_{o,\max} = E_{o,\Sigma}, \end{cases} \tag{2}$$

$$E_i < \overline{E} \Rightarrow \begin{cases} E_{o,\Sigma} = 0, \\ E_{u,\Sigma} = \sum_{i=1}^{n} (E_i - \overline{E}), \\ E_{u,\max} > E_{u,\Sigma} \Rightarrow E_{u,\max} = E_{u,\Sigma}, \end{cases} \tag{3}$$

where $E_{u,\Sigma}$ – energy of the under-consumption period; $E_{o,\Sigma}$ – energy the over-consumption period; $E_{o,max}$ – energy consumption at the highest over-consumption period; $E_{u,max}$ – energy consumption at the highest under-consumption period; E_i – energy amount at the moment i; $\overline{E}$ – average energy consumption.

The average daily electricity consumption is 1 kWh per hour. In Fig. 5 two important periods: over and under consumption period are shown for storage system dimensioning. The largest over consumption period is from 17 to 1 o'clock and the under-consumption period is from 1 to 7 o'clock with energy amounts of 4.5 kWh and 4 kWh, respectively.

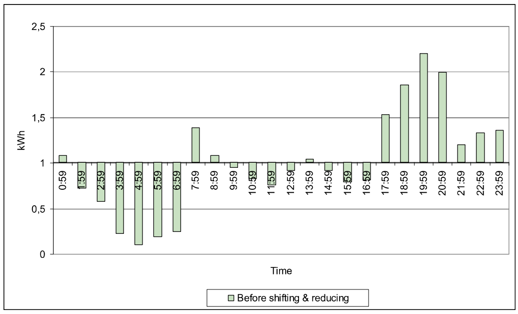

Fig. 5. Average daily electricity consumption before shiftable loads scheduling

To obtain a more precise overview holiday and workday consumption should be analyzed separately. Fig. 6 shows that at holiday one large over- and under-consumption period occurs. The largest over-consumption period is from 11 to 21 o'clock with an energy amount of 10 kWh. The largest under-consumption period is from 23 to 11 o'clock with an energy amount of 9.7 kWh. By an average consumption deviation of 25%, over- and under-consumption energy amounts are about 7 kWh and 5.7 kWh, respectively.

It is shown in Fig. 7 that at workdays two over- and two under-consumption periods occur. Over-consumption periods are from 7 to 10 o'clock and from 17 to 1 o'clock with an energy amount of 2 kWh and 5.4 kWh, respectively. Under-consumption periods are from 1 to 7 o'clock and from 10 to 17 o'clock with an energy amount of 3.5 kWh and 3.9 kWh, respectively.

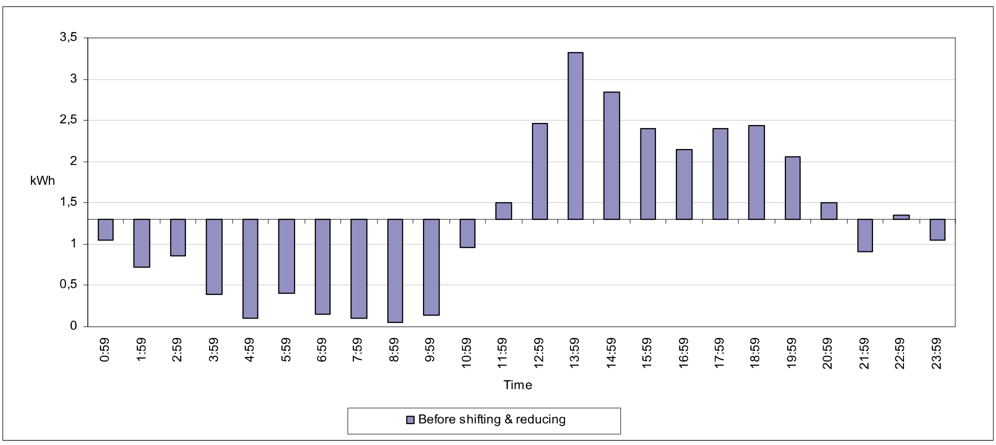

Fig. 6. Average holiday electricity consumption before shiftable loads scheduling

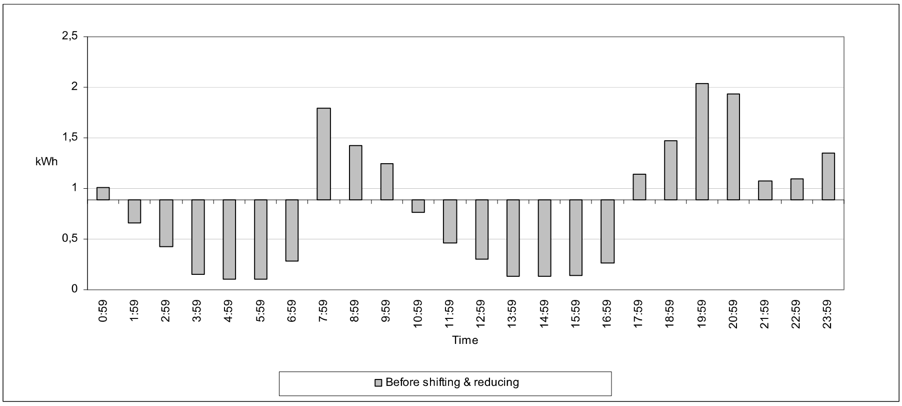

Fig. 7. Average workday electricity consumption before shiftable loads scheduling

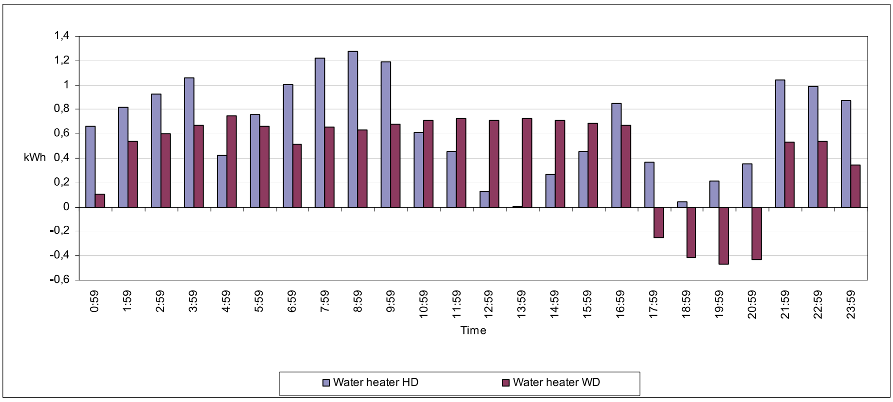

Fig. 8. New consumption pattern for water heater HD and WD consumption

Electrical energy storage capacitance should be greater than or equal to the highest energy consumption period. Comparing the energy consumption of a workday, holiday and average day, the maximum energy demand for balancing is about 7 kWh.

Consumption balancing with water heater consumption shifting

This section analyzes the use of a water heater for electricity consumption balancing in a two-tariff system. Using a simplified formula (4) the consumption pattern of a new water heater for balancing is calculated:

$$E_{i,awh} = E_{i,bwh} - (E_{i,b} - \overline{E}); \quad E_{i,awh} < 0 \Rightarrow E_{SE} = \left| \sum_{i=1}^{n} E_{i,awh} \right|, \quad (4)$$

where $E_{i,awh}$ – water heater energy consumption after shifting at time i; $E_{i,bwh}$ – water heater energy consumption before shifting at time i; $E_{i,b}$– total energy consumption before shifting at time i; $\overline{E}$ – average energy consumption; E_{SE} - shortage of energy, which should be balanced by the electrical energy storage.

Fig. 8 shows that consumption scheduling with water heater can balance electricity consumption on holiday. Also, no problems are encountered in consumption balancing with water heater scheduling at workday from 0 to 17 and 21 to 24 o'clock.

As shown in Fig. 8, it is not possible to balance consumption between 17 and 21 o'clock with a water heater. At the same time another high consumption unit, the cooking stove, is used. During that period the shortage of energy is about 1.6 kWh (0.4kWh per hour), which should be supplied by an additional electrical energy storage system or energy source. An alternative is to reduce comfort level by shifting or reducing of other non-shiftable loads consumption.

Conclusions

The minimum energy reserves that an electrical energy storage system should have for described household energy consumption:

- Shifting, based on the two-tariff system, 4.9...6.9 kWh;
- Shifting, based on the Nord Pool Spot (NPS) average daily price, 4.83....11.8 kWh;
- Balancing, if shiftable loads consumption is not separately shifted, 5.4...10 kWh;
- Balancing, if shiftable loads consumption is separately shifted, 1.6 kWh.

As described above, an electrical energy storage system should have energy reserves of approximately 5 to 10 kWh. The peak-power of an electrical energy storage system should be chosen in most cases between 2 to 7 kW, depending on functionality and consumption patterns. Electrical energy storage with such parameters can be used in most energy consumption balancing and shifting cases.

Similarity of the calculated parameters of household energy storage with the parameters of existing hybrid electric vehicle batteries makes the technology used in vehicles attractive for residential areas. Profitability of DSM (demand-side management) systems for loads priority based scheduling [8][9], using an electrical energy storage, is questionable.

The feasibility of investment to different control systems and models depends on customers habits. For small customers/households often very simple and fast profitable energy consumption costs reduction (for example in household device integrated scheduling functionality) solutions exists.

Optimization of electrical energy storage charging/discharging cycles according to realtime dynamic prices is an important topic for further research. Dimensioning of electricity storage according to production of micro-scale renewables (in residential area and housholds) is another important topic for furher research.

Acknowledgements

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A. Rosin, A. Auvaart, D. Lebedev. Analysis of Operation Times and Electrical Storage Dimensioning for Energy Consumption Shifting and Balancing in Residential Areas // Electronics and Electrical Engineering. – Kaunas: Technologija, 2012. – No. 4(120). – P. 15–20.

This article describes operation times of home appliances and energy consumption based electrical energy storage dimensioning analyses for residential areas. The analysis is based on an object in Estonia. The electrical energy storage dimensioning for consumption scheduling in the two-tariff system and on the basis of the Nord Pool Spot (NPS) price is discussed. Additionally, in the storage dimensioning part, consumption balancing using of electrical energy storage and water heater consumption shifting is analyzed. Optimization of electrical energy storage charging/discharging cycles according to realtime dynamic prices is an important topic for further research. Ill. 8, bibl. 9, tabl. 1 (in English; abstracts in English and Lithuanian).

A. Rosin, A. Auvaart, D. Lebedev. Elektros energijos talpyklų eksploatacijos trukmių parametrizavimo analizė siekiant subalansuoti elektros suvartojimą gyvenamosiose vietovėse // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2012. – Nr. 4(120). – P. 15–20.

Pateikti buitinės technikos eksploatacijos trukmių ir energijos suvartojimo analizės rezultatai. Aptartas elektros energijos talpyklos parametrizavimas suvartojimui planuoti dviejų tarifų sistemoje. Analizuojamas vartojimo subalansavimas naudojant elektros energijos talpyklą ir kaitinimui sunaudoto vandens postūmį. Elektros energijos talpyklos įkrovimo ir iškrovimo ciklų optimizavimas, atsižvelgiant į kainų kitimą, yra tolesnių tyrimų sritis. Il. 8, bibl. 9, lent. 1 (anglų kalba; santraukos anglų ir lietuvių k.).

Paper IV

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Energy storage dimensioning and feasibility analysis for household consumption scheduling based on fluctuations of Nord Pool Spot price

***Abstract**. This paper describes the analysis of price fluctuations in the Nord Pool Spot (NPS) Estonia (EE) area. Also the electrical energy storage dimensioning and feasibility analysis for consumption scheduling on the basis of the NPS EE area price is discussed.*

***Streszczenie.** W artykule przedstawiono analizę fluktuacji cen na obszarze objętym przez Nord Pool Spot (NPS) Estonia. Dodatkowo zaprezentowano metody wymiarowania oraz analizę wykonalności układów magazynowania energii na podstawie danych dotyczących zużycia energii w systemie NPS EE. (**Wymiarowanie i analiza wykonalności magazynów energii dla obiektów mieszkalnych na podstawie fluktuacji cen w Nord Pool Spot**).*

Keywords: consumption scheduling; household; Nord Pool Spot; energy storage dimensioning; feasibility.
Słowa kluczowe: in the case of foreign Authors in this line the Editor inserts Polish translation of keywords.

Introduction

The deregulation of electricity industry is giving way to global trends toward the commodization of electric energy. [1][2]. This trend has intensified in Europe and North America, where market forces have pushed legislators to begin removing artificial barriers that have shielded electric utilities from competition. The price of electricity is far more volatile than that of other commodities normally noted for extreme volatility. Relatively small changes in load or generation can cause large changes in price and all in a matter of hours (with real-time dynamic prices in seconds or minutes). Unlike in the financial markets, electricity is traded every hour of the year - including nights, weekends and holidays. Unlike other commodities, electricity cannot be stored efficiently. Therefore, delicate balance must be maintained between the generation and consumption for 8760 hours a year.

There is, however, a great difference between electricity and the other energy (and commodity) markets in that the variable costs of production vary so greatly between different types of installation – Wind and Hydropower with a virtual nil cost at one extreme and Gas Turbines at the other end of the scale. In order to satisfy fluctuating consumer demand at the lowest cost, a broad variety of generating techniques are required. Some installations are capital intensive but can be run year round and are relatively fuel efficient (hydro, nuclear, coal-fired). Other units such as co-production of heat and power are used less frequently to cover winter heating demand at times of higher prices. Whilst energy intensive units such as Gas Fired Turbines are used for brief periods of very high price and demand.

Although the principle of generation electricity is simple, generating electricity for an area as large as Europe means a complex balancing process. One of the biggest problems faced by the system operator is congestion. When congestion occurs, zonal prices supersede power exchange's market clearing price, which is based on the aggregated energy supply and demand curve intersection point for each hour [3]. In such a case, electricity prices can increase or decrease dramatically. The primary role of a market price is to establish equilibrium between supply and demand. This task is especially important in the power markets because of the inability to store electricity efficiently and the high costs associated with any supply failure. NPS runs the largest market for electrical energy in the world, offering both day-ahead and intraday markets to its participants. 330 companies from 20 countries trade on the Exchange. In 2009 the NPS group had a turnover of 288TWh [4]. The spot market at NPS is an auction based exchange for the trading of prompt physically delivered electricity. The spot market carries out the key task of balancing supply and demand in the power market with a certain scope for forward planning. In addition to this, there is a final balancing process for fine adjustments in the real time balancing market. The spot market receives bids and offers from producers and consumers alike and calculates an hourly price which balances these opposing sides. NPS publishes a spot price for each hour of the coming day in order to synthetically balance supply and demand. Every morning Nord Pool participants post their orders to the auction for the coming day. Each order specifies the volume in MWh/h that a participant is willing to buy or sell at specific price levels (€/MWh) for each individual hour in the following day. The SESAM (Elspot trading system) calculation equation (1) is based on an application of the social welfare criteria in combination with market rules. SESAM is maximizing the value of the objective function subject to physical constraints; like volume constraints, area balances, transmission and ramping constraints.

$$Max \sum_{n} \left\{ \int_{0}^{d^a} D^a(x)dx - \int_{0}^{s^a} S^a(y)dy \right. \tag{1}$$

where a – represents an area, d^a – demand in the area a, and D^a – demand function in the area a, s^a – supply in the area a, S^a – supply function in the area a, and n – number of areas.

The system price (SP1) for each hour is determined by the intersection of the aggregate supply and demand curves which are representing all bids and offers for the entire Nordic region [4]. In addition to area price there is also an annual fixed fee and a variable trading fee for all market participants. In the political debate surrounding energy, this type of price formation is labeled a marginal price setting. This gives a false impression that the establishment of prices in the electricity market is different from the price formation process in other commodity markets. The only difference lies in the significantly higher requirements for the secure delivery of electricity because it must be delivered at the precise moment it is needed by the consumer. The inelasticity caused by the inability to store electricity is the reason of this difference.

Storage dimensioning for consumption scheduling based on the Nord Pool Spot (NPS) average daily price

To find the possibilities for consumption scheduling it was constructed an average day from actual data from the NPS trading system. It was studied a period of seven months starting in April 2010. Average price was calculated with the well-known formula of a generalized mean.

$$\bar{x} = \sqrt[m]{\frac{\sum_{i=1}^{n} x_i^m}{n}} \qquad (2)$$

where X_i – price of electrical energy at time i

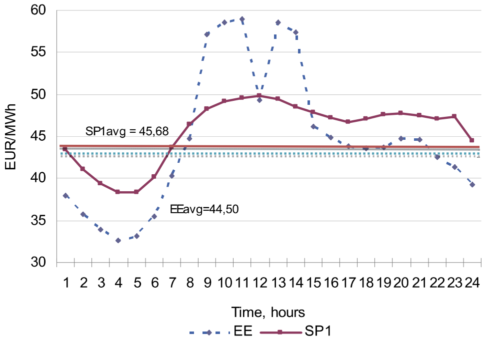

Fig. 1. Average daily price at the EE area and SP1 area

One hour is the smallest time interval when prices can change, because on spot electricity trading prices are set constant for delivery of power during a certain hour. Analysis shows that fluctuations in the system area are smaller (around 11.00€/MWh) than in the EE area (the amplitude of the price during the day is much higher at 26.35€/MWh) (Fig. 1). The high price amplitude in the local market provides opportunities to use consumption scheduling models in residential areas to gain economy.

Energy consumption in households in the UK is reported in [5] and in Estonia in [6]. Peak hours for UK households are from 06-08 and 13-18. Main peak hours for Estonian average households are at 7-8 and 19-21 on workdays (WD) and 12-14 and 19-21 at weekends (HD). It is quite easy to see the possible use of energy storage to smoothen the loads at morning or midday use and even the evening use at weekends. However, some exact calculations are needed in terms of the possibilities to conserve energy at low price before evening peak hours on workdays [7].

According to equation 2 the average NPS price during the measured period (April 2010 to October 2010) in the Estonia (EE) area is calculated as 44.50€/MWh. The NPS price curve is not similar on workdays and at weekends. The maximum price on workdays is 65.93€/MWh and the minimum is 33.35€/MWh. At weekends the maximum and minimum prices are 43.05€/MWh and 29.76€/MWh, respectively. Average price below the EE area average (44.50€/MWh) is 38.02€/MWh (-14.55%) on workdays and 38.26€/MWh (-14.03%) at weekends. Average price above the EE area average is 53.50 €/MWh (20.22%) on workdays and does not exceed the average at weekends.

If all shiftable loads on workday (WD) are "switched on" under average price, then at least 1.1 kWh storage system is needed for shifting of energy consumption (Fig. 2).

If all shiftable loads on holiday (HD) are "switched on" under average price, then at least 11.8 kWh of energy consumption should be supplied from the storage system (Fig. 3). If an average price deviation is allowed (43.05 - 29.76)*10% = 1.33€ (10 % from maximum and minimum price difference), then 4.83 kWh should be supplied from the electrical energy storage.

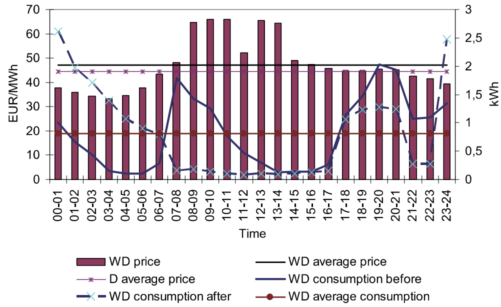

Fig. 2. Average workday price fluctuation compared to electricity consumption before and after scheduling of shiftable loads

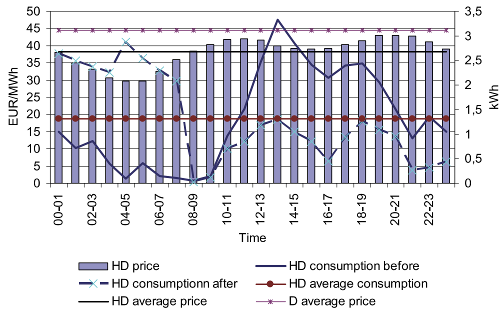

Fig. 3. Average holiday price fluctuation compared to electricity consumption before and after scheduling of shiftable loads

Average price deviation and distribution of price range

As shown on figure 4, the deviation calculated by the simple formula (3) from the average price to analyze possibilities to use off-peak hours to store energy or shift the load to off-peak hours. We needed an assurance of off-peak hours available to recharge the batteries or other storage equipment. We found that the average duration of peaks that are higher than the average area price is 9.59 hours and the average duration of off-peaks is 13.48 hours. That means there is plenty of time to recharge storage equipment during the off-peak time.

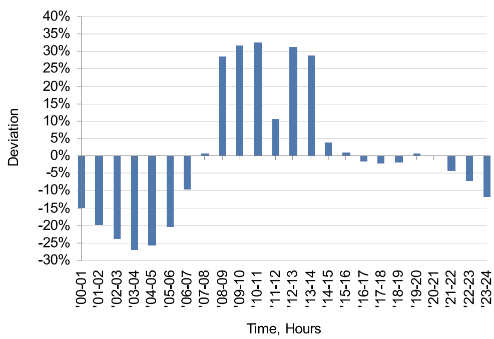

Fig. 4. Average EE area price deviation

Deviation from an average price is higher at peak hours, but peak hours last less than off-peak hours. It is most profitable to save energy between the 23...06 o'clock, then the price is lower than 10% compared to average. There is also a possibility to save energy between 16...19 o'clock when the price is about 2-3% lower than average.

$$S = \frac{\sum_{n=1}^{k} \frac{x_i}{n} - X_F}{X_F} \tag{3}$$

where X_i – price of electrical energy in the instance i (from 0-24 hours), and X_F – average area price.

As seen in fig. 5 the distribution of prices is symmetric and leptokurtic. With the leptokurtic distribution, the price will have a relatively low amount of variance, because return values are close to the mean. This could mean that energy producers will not try to invest to storage facilities as there could be quite small return on investment. This gives us an opportunity to continue our research on the profitability of using energy storing and shifting on the demand side.

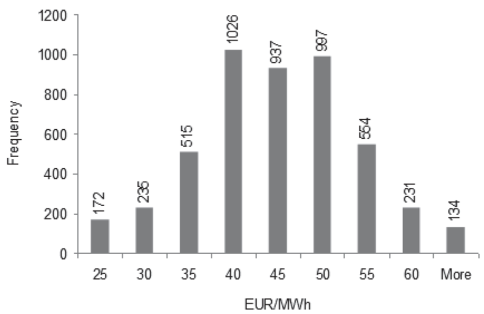

Fig. 5. Distribution of price range in the EE area

Feasibility analysis

Today batteries could be the best solution for consumption shifting in an average apartment [6]. Their feasibility for households can be estimated by the system cost and profit calculation. To find a profitable ES, it is necessary to take into account parameters and costs described in papers [8] and [9]. In current analysis are described Lead-Acid (LA), Nickel Cadmium (NiCd), Lithium Ion (LiIon), Sodium Sulphur(NaS), Vanadium Redox Flow(VR), Polysulfide Bromide Flow (PSB) and Zinc Bromide (ZnBr) batteries.

10 year usage of energy storage (1 charge/discharge cycle per day) will give approximately 3650 cycles then charging takes place in the low price period at night and discharge takes place in the high price period during daytime. In case of constant Depth of Discharge (DoD) value, the required energy capacity is different from initial energy capacity. The simple equation 4 establishes the final required energy capacity for consumption scheduling with particular DoD.

$$E_{1,\max} = \frac{E_I}{DoD} \tag{4}$$

Where $E_{1,max}$ – required maximum energy capacity, and E_I – initial required energy capacity.

Table 1 shows the result of DoD and energy capacity calculation with 3650 cycles for different batteries with 7 and 12 kWh of Initial Required Energy Capacity (IREC). It shows that highest discharge depth can be applied in case of NaS battery, which reduces the final required energy capacity until 7.68 kWh. Thus, daily maximum load shifting to low price involves one charging/discharging cycle of ES with 7 kWh of energy capacity. Daily cost savings C_{cyc} for one charge/discharge cycle with estimated price deviation are shown in (5).

$$C_{cyc} = E_{2,\max} \cdot \Delta x \tag{5}$$

where E_{2max} – ES maximum energy capacity for financial saving, Δx – amplitude of price during the day (26.35€/MWh).

Table 1. DoD and energy capacity calculation with 3650 cycles

	Li-Ion	LA	NiCd	ZnBr	VR	NaS
DoD, %	72,76	14,58	43,63	45,62	76,66	91,10
IREC 7 (kWh)	9,62	48,02	16,04	15,34	9,13	7,68
IREC 7 (kWh)	16,49	82,32	27,50	26,31	15,65	13,17

The result of equation 5 is 0.186 € (7 kWh x 0.0264 €/kWh). It means that one charging/discharging cycle of ES for investigated apartment will save 0.19€

Table 2 demonstrates ES total cost calculated for initial required energy capacity of 7 kWh and peak power 7 kW. There are columns with calculated number of cycles for investment return and costs per 1 cycle. The last column of table 2 is price difference multiplying factor. It shows by how many times current price difference must be increased for ES recoupment. As we can see none of batteries storages is able to return the investment and make profit within current life-time (cycles). It means, with current price differences, there are only two opportunities to achieve profitability. The first one is reducing the total cost of energy storage system (cheaper components, cheaper maintenance), which should give possibility to return investment in limited period of time i.e. 7 – 10 years. The second method is increasing lifetime of ES (more cycles, higher efficiency), which should give possibility to return investment in period of time about 20 – 30 years, before it fails or breaks down.

According to table 2 the most prospective ES is Sodium Sulphur (NaS) Battery. It has medium energy capacity cost and slightly expensive power capacity cost (up to 380€ / kW). While it is quite new product on the market, the cost could be reduced. Today, the main difficulty is that developing companies generally target this technology for utility-scale (>1000 kW) stationary applications. Developing of NaS system solutions for small consumers can bring this type of storages to households market.

The increasing usage of renewable energy sources (and/or increasing production of renewable sources) on the market could increase price differences and profitability of ES systems. Also, introduction of full real-time dynamic pricing system (e.g. price changing period is 5 minutes or less), with increased amplitude of price, could reduce profitability time of electrical ES systems for households.

Table 2. Investments return calculation for battery energy storages

Battery type	Energy storage cost €	Cost per cycle €	Amount of required cycles to return the investment	ES actual lifetime cycles with DoD 50%	Price difference multiplying factor to return investments with lifetime cycles
NaS	4109	0,41	21625	10000	2,2
LA	3399	8,94	17889	380	47,1
NiCd	7948	2,65	41833	3000	13,9
Li-Ion	6772	0,97	35642	7000	5,1
ZnBr	3161	0,93	16635	3400	4,9
PSB	3979	0,99	20944	4000	5,2
VR	3394	0,64	17862	5300	3,4

Conclusion

We observed the EE area price during 4802 hours starting from 1 April 2010 when Estonia entered the NPS market. During that time an average hourly price for the EE price area was 44.5€/MWh and it is slightly lower than the price in the system area. The price curve is similar on weekdays and at weekends. At weekends the average hourly price remains under an average area price. An average off-peak time lasts for 13.48 hours, which is long enough to store energy with cheaper storage equipment or shift the power usage to a less expensive time period without losing customer's comfort requirement. The minimum energy reserves that an electrical energy storage system should have for described household energy consumption shifting, based on the Nord Pool Spot (NPS) average daily price should be between 4.83....11.8 kWh (average about 7 kWh).

Described analysis shows that there is no ES solution for a household which would return total initial investments and make a profit in a lifetime period. With current battery lifetimes and current DoDs, battery storages will bring profit only with the difference growing between energy prices by 2.2 for NaS as a minimum and by 47.1 for LA as a maximum one. Nevertheless, the similarity of the calculated parameters of household energy storage with the parameters of existing hybrid electric vehicle batteries makes the technology used in vehicles attractive for residential areas. Today, the most feasible solution is load shifting with simple scheduling systems (without electrical energy storage). Profitability time of investments for simple scheduling systems is up to 2 years. For example, investment for the shifting equipment of water heater is less than 1 year.

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Paper V

Lebedev, D.; Rosin, A. (2014). Modelling of Electricity Spot Price and Load Forecast Based New Energy Management System for Households. 55th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga Technical University, Riga, October 14, 2014. Latvia: IEEE, 222−226.

Modelling of Electricity Spot Price and Load Forecast Based New Energy Management System for Households

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Abstract **– The aim was to determine probable profit by using an electric energy storage (EES) device in a typical household. Focus is on theoretical and practical studies of an energy management system (EMS) based on VRLA battery storage. Use of a battery charge-discharge-schedule (BCDS) enables an optimal operation of EES taking advantage of the low price periods by importing more energy and storing it, while reducing the imported power during high price periods by supporting the load with the stored energy. Forecasted price and load are used to optimize the BCDS of EES, at the same time ensuring load demand supply. In the day-ahead market, the management system uses the mathematical functions to calculate the price of imported energy in each period of time with the day-ahead forecasted price and typical load in the household. The recursion loops in the optimization algorithm search for the best BCDS to reach the highest profit for the end consumer. All the calculations will be tested on the EMS to confirm the theoretical part.**

Keywords **– Battery storage, EES, energy management system, power system economics, smart grids, Time Of Use energy price.**

I. Introduction

The present ecological, economical and political situation leads to a significant growth of renewable energy sources in electricity production. Fluctuation of the energy cost, as well as recent liberalization of electricity market and incentive policies to support renewable sources and hybrid systems (EES in smart grids), offer exciting opportunities to the owners of these systems to reduce their electricity bills. Our aim here is to ensure load demand supply at the lowest cost, at the same time considering the limits of the system. To fulfill this task, an optimized hybrid EMS was developed. Term "hybrid" means that load demand is met by the grid power and/or power of the EES. This gives flexibility and reliability to the system. We propose a simple deterministic approach that ensures an optimal use of EES. A scheme of the system is shown in Fig. 1. This notation serves as a reference in the paper. Regarding to actual constraints of the grid, the connected battery bank is not allowed to feed the grid. Subsequently, the storage is used only to support load demand. In our system, the load is assumed to be inelastic with respect to the energy cost. On the other hand, the charging and discharging operations of EES are controllable and flexible. As imported power is comprised of the load and the EES charging or discharging operation, imported power is elastic to some level because of the flexibility of the EES operation. The EES software control is designed by its operation parameters, including minimum and maximum energy storage capacity, discharging current limit, charging current limit, and charging efficiency [1].

II. Related work

Recent developments include a number of new approaches to minimize electricity bills in households by using electric energy storage. Under household, here, we mean apartments and small individual houses. Technical and economic literature on electric energy storage describes various storage applications that are partly overlapping. The optimization methods analyzed were: Model Predictive Control [1], deterministic approach [2], particle swarm optimization [3], linear optimization methodology [4], dynamic optimization, and Taguchi Method [5]. Some of the methods use optimization structures that are very complicated for household implementation. Several approaches are insufficiently flexible for use without PV or wind turbines, which also makes them useless in households without solar or wind sources. Mathematical functions for the EMS were developed taking into account the theoretical model of a battery [6]. The main benefit of this work is in the simplicity of the optimization algorithm.

III. System description

Energy management system (EMS) is a mix of hardware devices and software solutions. Thus, the main subcategories of the system are hardware and software of the stand

A. Hardware

The hardware of the EMS is a compilation of different subsystems with various tasks. It consists of four parts: Personal Computer (PC), Programmable Logic Controller (PLC), Load and Power Unit (PU). Power Unit is a complex device from the Victron Energy Company. The basic element of this device is a 3 kW Inverter of Quattro series. The Quattro unit is a battery inverter and a charger combined in one unit. Selection of the inverter based on the price, it is cheaper comparing to competitors and time of delivery. Off-grid power systems with this inverter can operate multiple electrical loads without overloading the AC power source, and deliver continuous uninterrupted power at power failure. Each Quattro is a true sine wave inverter, meaning clean power for sensitive electronics. It is also a sophisticated battery charger

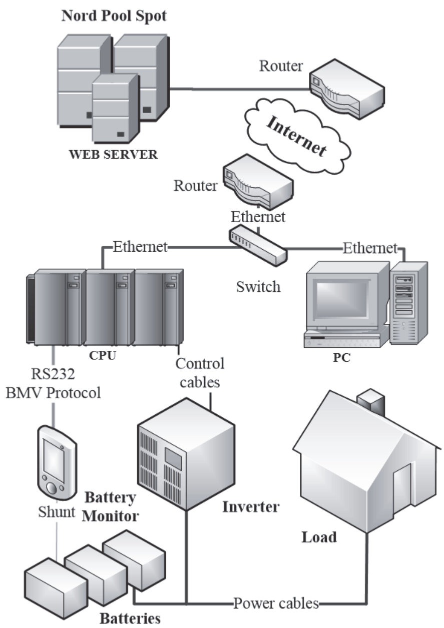

Fig. 1. System configuration.

that features an adaptive charge technology. The batteries used in the PU are Deep cycle AGM batteries 12VDC with a total capacity of 880 Ah. The inverter acquires all the required values from batteries via the Precision Battery Monitor (BMV). The BMV is a device that monitors PU battery status. It measures battery voltage and battery current constantly and uses this information to calculate the actual state of the charge of the battery bank. The last basic element of the PU is the Digital Multi Control panel (DMC), which allows limiting grid input current and monitoring basic status of the inverter.

The PLC of the system is Siemens CPU of S7-1200 series. It is a line of PLCs that can control a variety of automation in industry and household applications. Siemens was chosen because of connection features of this CPU. This smart controller makes On/Off switching of the load groups during working hours. It was made to simulate real load of a typical household consumption during 24h. Therefore, the Central Processing Unit (CPU) of the controller has two databases with 24 records each, corresponding to 24 hours of the typical average load consumption in households [7]. A representative household load for a workday is shown in Table 1. The first database represents a workday's and the second a weekend's consumption. Another main task of the PLC is to control the battery charge-discharge-schedule according to the profile data transferred from the PC.

The PC subsystem of the project hardware fulfills an important function by optimizing the BCDS to receive the highest profit with the use of EES and fluctuating spot prices. Optimization takes place at 12.00 UTC and creates a battery schedule for the next 24 hours. To achieve this, a special application

TABLE I

AVERAGE LOAD ENERGY CONSUMPTION AND FORECASTED PRICE DISTRIBUTION DURING WORKDAY [7]

Hour	kWh	€/kWh	Hour	kWh	€/kWh
0:00	1.482031	0.0330	12:00	0.463861	0.0419
1:00	1.101665	0.0328	13:00	0.299279	0.0427
2:00	0.729638	0.0329	14:00	0.135066	0.0461
3:00	0.465483	0.0337	15:00	0.143417	0.0478
4:00	0.155727	0.0357	16:00	0.149556	0.0477
5:00	0.108135	0.0451	17:00	0.279366	0.0425
6:00	0.106064	0.0443	18:00	1.188915	0.0392
7:00	0.290092	0.0439	19:00	1.620046	0.0385
8:00	1.900813	0.0395	20:00	2.261207	0.0380
9:00	1.496892	0.0390	21:00	2.194288	0.0429
10:00	1.274349	0.0390	22:00	1.318521	0.0687
11:00	0.770185	0.0395	23:00	1.327011	0.0348

loads the forecasted prices from the internet for each hour of the next day. The PC also has Human Machine Interface runtime application and saves the main system variables to the SQL database on the hard drive inverter.

The system includes 15 bulbs for a typical household load simulation, i.e. a general power of 3 kW. The PLC interpolates load values in accordance with 24h load array. This means that the CPU takes the maximal value from the load array and divides it to 4 bit; it gives a value to each bit and a bit combination allows simulating the load ranging from zero to maximum power.

B. *Software*

The main software programs are written for PLC and PC. The PLC program was developed in Siemens Totally Integrated Automation (TIA) Framework and presents the mix of the functions written in Ladder Logic (LAD) and Structured Control Language (SCL). The reason why SCL is used is because of some complicated communication functions, which are impossible to implement in pure Ladder Logic. PLC program implements communication between the CPU and the Battery Monitor with the help of the BMV protocol. It requests the main parameters of the batteries and converts them to ASCII data with service characters. CPU accepts this protocol on the RS232 layer. General input data for optimization algorithms like Nord Pool Spot forecasted prices and output data like batteries charge-discharge-schedule are read by PLC over Ethernet connection. Communication is based on the classic Master-Slave/Send-Receive relations. The PLC has the Slave role in this network topology and reads the data from the PC, which acts like Master. These assignments result from the fact that the CPU processes runtime program in cyclical rather than in eventual mode. This means that data are being requested over the network cyclically, which causes overloads of the communication channel. Also, Ethernet connection is used to transfer Battery Monitor data from the PLC to the Human Machine Interface (HMI) visualization program. The HMI is projected in the Siemens development environment WinCC Flexible 2008. The main task of the HMI is to acquire BMV data (V, I, SOC tags) and archive them to the SQL database. The system updates tag values every second and saves their mean values to the database every 30 seconds. Another job of the HMI is to control load groups in the manual mode. For this purpose it has graphical elements, like buttons and switches. The second runtime system in the PC is the application, which is responsible for the battery charge-discharge-schedule optimization. It is the core of the whole EMS system. This application is written in high level object oriented language C#. It can communicate with internet protocols and make requests from Nord Pool Spot for new forecasted prices every day. Afterwards it uses this data in the optimization algorithm to find out the best (which means more profitable) charge discharge schedule for the battery bank. When the schedule is ready, the core application sends the schedule data to the CPU. This action is an event and takes place only once during 24h, which is more resource-saving for network traffic than cyclical acquisitions of the CPU. Thus, the control of the workbench stand is divided into two parts: the calculation/processing in the PC and executing/running in the PLC.

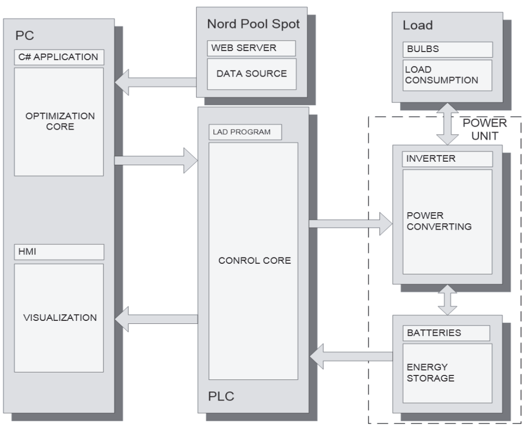

Fig. 2. Main system parts and data flow directions.

IV. Algorithm

The algorithm for searching for the most profitable battery charge-discharge-schedule is based on a loop optimization routine. In the beginning, the core application sends a request for the forecasted Nord Pool Spot energy prices for the next time period at 12:00 UTC. The time period consists of T timeslots t with $t = 1...T$, where T=24 hours. The daily sum cost $C_{T=24h}$(1) without use of the EES, considering only forecast prices and conditions (2),

$$C_{24h} = \sum_{t=1}^{T} (P_{grid}(t) \cdot Fp(t)), \quad (1)$$

$$\begin{cases} P_{grid}(t) > 0 \\ P_{grid}(t) = P_{load}(t) \end{cases}, \quad (2)$$

where P_{grid} is power from the grid; P_{load} is load consumption; Fp is forecasted electricity price €/kWh. The real time stochastic fluctuation of the price during the time period is not considered in this work. The EES suits only with the constraints of the battery: the state of charge (SOC) has to be within the range of its minimum and maximum allowed values. The charging and discharging currents have to be within their boundaries. Power loss of the charging operations is considered in the charging efficiency. During the operation, storage level at the end of each period is determined by the storage level of the previous period and the charging or discharging operation in this period [8]; it is expressed in(3)

$$SOC(t) = SOC(t-1) + x_1 \cdot \eta \cdot P_C(t) - x_2 \cdot P_D(t), \quad (3)$$

where P_C is the charging power, P_D is the discharging power, $SOC(t)$ is the energy storage level at the end of period t, η is the charging efficiency, $x1$ and $x2$ are charge/discharge decision variables. All the variables must be within their operation limits, expressed as

$$0 \le P_C(t) \le P_C \max; \quad (4)$$

$$0 \le P_D(t) \le P_D \max; \quad (5)$$

$$SOC \min \le SOC(t) \le SOC \max; \quad (6)$$

$$charging: x_1 = 1, x_2 = 0; \quad (7)$$

$$discharging: x_1 = 0, x_2 = 1. \quad (8)$$

Depth of Discharge (DOD) of Deep cycle AGM batteries is recommended to be less than 40%, thus we consider *SOC*min as 60% and *SOC*max as 100%. The 40% of discharge is equal to 3 kWh in our case. It means that the Quattro inverter can support a load consumption of 3 kW during one hour only with battery energy. Charging power is calculated by the current measurement and integrating it by time

$$P_C(t) = \int_{t-1}^{t} i(x)dx = u\int i(x)dx = \sum_{ts=1}^{60} i(ts) \cdot u, \quad (9)$$

where i is the charging current from the grid, u is the grid voltage and ts is the time period which equals t/60. If battery parameters and values are known, then the core system searches for profit by using EES and criteria for selection are presented in (10)

$$\begin{cases} P_{load}(t) \cdot Fp(t) - (P_{load}(t_n) + P_{load}(t)) \cdot Fp(t_n) \ge 0 \\ T > t_n > t \end{cases}, \quad (10)$$

where t_n is the next time period with regard to current time period t, which is less than maximum time slot 24, corresponding to 14:00 PM. To achieve correct load distribution in the array, the sort function is called, which merges the forecast prices with 24 hours load array from Table 1. When the table is ready, the Profit Matrix (PF) function is called. It has main control loop with one sub loop, which operates on the basis of (10). This combination allows all hours t to be found from the 24 h array, when discharging the battery is more profitable than using grid electricity, and charging battery back in different hours will lead to electricity cost saving, which means profit for consumers. When the PM is filled, the recursive function starts to search all correct hour (correct means discharging hour takes place before charging back hours) combinations p (1..*max*) and makes a sortable list from them. The final function sorts this list by maximum profit value and selects the highest one. Thus, considering that one possible profit from the charging/discharging combination is as described by (11) and the maximum day profit *DayP* is as follows from (12).

$$p = P_{load}(t) \cdot Fp(t) - (P_{load}(t_n) + P_{load}(t)) \cdot Fp(t_n) \quad (12)$$

$$DayP = MAX(\sum_{i=1}^{i_{\max}} P_i = (P_{load}(t) \cdot Fp(t) - - (P_{load}(t_n) + P_{load}(t)) \cdot Fp(t_n)). \quad (13)$$

When the maximum profit is found, the application assembles a telegram for PLC, which consists of discharge hours and charge hours, and sends it by Ethernet to the CPU program. It creates a schedule for the load and battery control on the PLC side.

V. RESULTS

To show our calculation example, the workday of Thursday 19.11.13 was chosen. Forecasted prices were loaded from the Nord Pool Spot web server. Load array was the load pattern for a typical household on a workday. After processing the PM routine, the main core obtains cells with data values for searching the most profitable battery charge/discharge hour combinations with (12). Evaluation of the charge/discharge hours begins from 14 PM of East European Time. Recursion function lists total profit from the combinations from Matrix and searches for the maximum value combination array. This particular day schedule with the highest profit is: discharging batteries during 16-19, 22-23 PM and charging back during 2-3 AM (13)

$$DayP = p_{1(16)} + p_{2(17)} + p_{3(18)} + p_{4(22)} = 0.00713 + + 0.01187 + 0.0466 + 0.09058 = 0.1561 \text{ €} \quad (13)$$

The distribution of prices and load curve with the use of EES is presented in Fig. 4. The hours with load consumption equals to zero indicated on the chart mean that energy for the load was taken from the batteries. Increased load curve values at other hours mean that additional load went for battery charging. Also, calculations for the weekend day – Saturday, 23.11.13 gave profit in 0.1734 €.

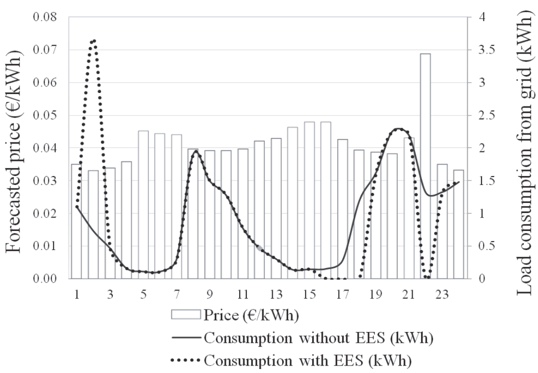

Fig. 3. Load and prices distribution with and without use of EES for Thursday 19.11.13

VI. CONCLUSION

Theoretical calculations show that profit from the use of EES for one day is not high; however it can increase with a boost of load consumption or at price swing growth during the day. On the other hand, we need to take into account investments in the system and battery ageing; we will do it in future work. One of the main improvements in this energy management system is a more flexible use of SOC of the batteries. It can be adjusted with a special variable anytime according to battery requirements. Major improvements can be achieved by fine-tuning current limiting values during the charge/discharge process in the inverter. It was impossible on this stage of work because of the limited features in BMV ASCII Text protocol. Another advantage can be taken from real-time prices monitoring and quick system response to that. Also, possibilities for integration into the smart-grid systems can be explored, as both systems share some of the hardware components. This can increase functionality of both systems at reduced initial investment cost, allowing for improved project feasibility. After system improvement and upgrade, the management algorithm will be compared with other known algorithms for energy management.

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Paper VI

Lebedev, D.; Rosin, A. (2015). Practical Use of the Energy Management System with Day-Ahead Electricity Prices. 2015 IEEE 5th International Conference on Power Engineering, Energy and Electrical Drives (POWERENG), Riga, Latvia, May 11-13. IEEE.

Practical Use of the Energy Management System with Day-Ahead Electricity Prices

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***Abstract*—Our goal was to define a possible profit resulting from the use of batteries as an electric energy storage (EES) device in apartment buildings or small houses as typical households. Focus was on the theoretical and practical studies of an energy management system (EMS) and financial analysis of investments return. Use of a battery bank charge-discharge-schedule (BCDS) allows an optimal operation of EES. The benefits lie in importing and storing more energy at low price periods while decreasing the imported power from the grid at high price periods and dispatching the stored energy for load demands. The BCDS is optimized by help of the price and load forecast, at the same time guaranteeing load demand supply. Nord Pool Spot day-ahead market provides all required data for the EMS to evaluate the cost of imported energy in each period of time. The optimization algorithm creates the best BCDS to bring the highest profit to the end customer. The calculations were tested in a laboratory on the EMS to confirm the theoretical part.**

Keywords—battery storage; EES; energy management system; power system economics; smart grids; Time Of Use energy price

I. Introduction

In the current economic and ecological conditions and policies, the share of renewable energy sources has increased remarkably in the production of electricity. A major advantage of today's owners of the hybrid systems, such as electric energy storage (EES) in smart grids, is in the reduction of electricity bills due to the recent liberalization of electricity market, incentive policies to support renewable sources and wavering of the energy cost. One of the aims of this research work was to ensure load demand supply at the lowest price taking into account the limits of the system. For the optimized hybrid, which means that load demand is met by the grid power and/or power of the EES, an Energy Management System (EMS) was designed and assembled. The hybrid device in the smart grid provides flexibility and reliability to the system. Two versions of the optimization algorithm have been created. They use a simple deterministic approach to complete an optimal use of electric energy storage. Concerning the actual constraints of the laboratory grid, the connected battery bank does not feedback the grid and the storage is used only to support the load demand. EMS constraints make the load inflexible with respect to the energy cost, but charging and discharging operations of EES are still controllable by the system algorithm. Operation parameters of an EMS, such as minimum and maximum energy storage capacity, discharging current limit, charging current limit, and charging efficiency, were considered during control software development [9].

II. Related work

Many studies cover electric energy storage and provide different approaches to reduce electricity bills in households. Technical and economic literature on electric energy storage describes various storage applications that are partly overlapping. Before composing the first version of the EMS core algorithm [1], we analyzed the following optimization methods: Model Predictive Control [1], deterministic approach [2], particle swarm optimization [3], linear optimization methodology [4], dynamic optimization, and the Taguchi Method [5]. Due to the complexity in implementation, only few of them are suitable for use in household energy systems. Many approaches are inflexible for use without PV or wind turbines, which also makes them inoperable in households without solar or wind sources. Mathematical functions for the first version of the optimization algorithm in EMS [1], as well as for the second, were developed taking into account the theoretical model of a battery [6]. The main advantage of our research system is in the simplicity of the optimization algorithm. We have already two versions of that algorithm. As compared to the first version, the second one has improved every-day profits from the electricity cost. In addition, all the calculations were tested by practical laboratory measurements.

III. System overview

An energy management system (EMS) is a mix of hardware devices and software solutions. It is divided to two main subcategories: hardware and software. Hardware consists of different devices, such as Personal Computer (PC), Programmable Logic Controller (PLC), Load, Inverter, Precision Battery Monitor (BMV), and batteries. The main functionality of the system is described by deep cycle AGM batteries 12VDC with a total capacity of 440 Ah. For the testing purposes, the system contains 15 bulbs to imitate household consumption, with a total power of 1.5 kW. The typical household load consumption is around 3 kW, but we scaled it two times lower to match our EMS power limits. The PLC interpolates load values in accordance with a 24 h load

TABLE I. AVERAGE LOAD ENERGY CONSUMPTION AND FORECASTED PRICE DISTRIBUTION DURING WORKDAY

Hour	*kWh*	*€/kWh*	*Hour*	*kWh*	*€/kWh*
0:00	0.741	0.02998	12:00	0.232	0.03322
1:00	0.551	0.02597	13:00	0.15	0.03282
2:00	0.365	0.02548	14:00	0.068	0.03265
3:00	0.233	0.02542	15:00	0.072	0.03664
4:00	0.078	0.02528	16:00	0.075	0.05255
5:00	0.054	0.02544	17:00	0.14	0.07437
6:00	0.053	0.02798	18:00	0.594	0.06342
7:00	0.145	0.03129	19:00	0.81	0.05409
8:00	0.95	0.03522	20:00	1.131	0.03252
9:00	0.748	0.03497	21:00	1.097	0.03163
10:00	0.637	0.03903	22:00	0.659	0.03087
11:00	0.385	0.03326	23:00	0.664	0,02778

array. The key control element in the system is the Siemens PLC of S7-1200 series. This logic controller has its own software inside switches ON and OFF of the load groups of the EMS during working hours. It was designed to simulate the real load of a typical household consumption during 24 h. For that reason, the Central Processing Unit (CPU) of the controller has two databases with 24 records each, corresponding to 24 hours of the typical average load consumption in households [7]. An average load in a small household and price distribution (according to Nord Pool Spot 11.11.14) for a workday is shown in Table 1. According to a previous analysis [7] in a real household, the hourly consumption could be at least 2 times higher).

PC software written in C# language optimizes the BCDS to receive the highest profit with the use of EES and fluctuating spot prices. Optimization takes place at 22.00 UTC when software requests day-ahead prices from Elering (Transmissioon System Operator – TSO) web site and creates a battery charge-discharge schedule for the next 24 hours. Human Machine Interface (HMI) visualization program acquires BMV data (V, I, SOC tags) and archives them to the PC SQL database. The system updates tag values every second and saves their mean values to the database every 30 seconds. Afterwards software implements these data in the optimization function to find out the best (which means more cost-effective) charge-discharge-schedule for the battery bank. When the schedule is ready, the core application sends it to the CPU. It creates a schedule for the load and battery control on the PLC side also. This action takes place only once during 24 h. Communication between PC and PLC software is shown in Fig. 1. Thus, the control of the workbench stand is divided into two parts: calculation/processing in the PC and executing/running in the PLC [1].

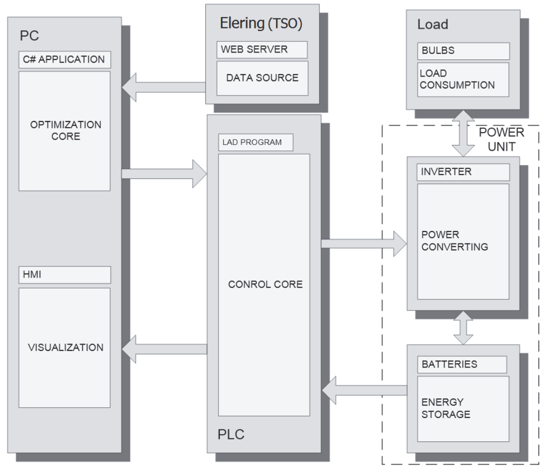

Fig. 1. Main system parts and data flow directions.

IV. ALGORITHMS

Both of the versions of the algorithms for searching for the most profitable battery charge-discharge-schedule are based on a loop optimization routine. Generally they use the same approach. In the beginning, the core application sends a request for the forecasted Nord Pool Spot energy prices for the next time period at 22:00 UTC.

These prices are located on the Elering TSO web site and are read from there by PC core software. The time period consists of T timeslots t with $t = 1...T$, where T=24 hours. The daily sum cost $C_{T=24h}$(1) without the use of EES, considering only forecast prices and conditions (2) is

$$C_{24h} = \sum_{t=1}^{T} (P_{grid}(t) \cdot Fp(t)), \quad (1)$$

$$\begin{cases} P_{grid}(t) > 0 \\ P_{grid}(t) = P_{load}(t) \end{cases}, \quad (2)$$

where P_{grid} is power from the grid; P_{load} is load consumption; Fp is forecasted electricity price, €/kWh. These conditions are valid for both algorithms. The constraints of the battery have been taken into account in this research work: the state of charge (SOC) has to be within the range of its minimum and maximum allowed limits. Similarly, the charging and discharging currents have to be within their boundaries [1]. Power loss of the charging operations is considered in the charging efficiency. During the operation, storage level at the end of each period is determined by the storage level of the previous period and, of course, the charging or discharging operation in this period [8]. It is shown in (3):

$$SOC\,(t) = SOC\,(t-1) + x_1 \cdot \eta \cdot P_C(t) - x_2 \cdot P_D(t), \quad (3)$$

where P_C is the charging power; P_D is the discharging power; *SOC(t)* is the energy storage level at the end of period *t*; η is the charging efficiency; *x1* and *x2* are charge/discharge decision variables. All the variables must be within their operation limits, expressed as

$$0 \le P_C(t) \le P_C \max ; \tag{4}$$

$$0 \le P_D(t) \le P_D \max ; \tag{5}$$

$$SOC \min \le SOC(t) \le SOC \max ; \tag{6}$$

$$charging : x_1 = 1, x_2 = 0 ; \tag{7}$$

$$discharging : x_1 = 0, x_2 = 1 . \tag{8}$$

For normal operation of the battery bank, the Depth of Discharge (DOD) of Deep cycle AGM batteries are recommended to be less than 40%. With our EMS power limits, it is sufficient to use 30%, thus we consider *SOC*min as 70% and *SOC*max as 100%. The discharge of 30% is approximately 3 kWh in our research work. It means that the Power Unit can support a load demand in 3 kW during one hour with pure battery energy. Charging power is calculated by the current measurement, integrating it by time

$$P_C(t) = \int_{t-1}^{t} i(x)dx = u\int i(x)dx = \sum_{ts=1}^{60} i(ts)\cdot u, \tag{9}$$

where *i* is the charging current from the grid; *u* is the grid voltage and *ts* is the time period which equals t/60. With battery parameters and values, PC core system searches for profit by using EES. The criterion for selection in the first version of the algorithm is presented in (10)

$$\begin{cases} P_{load}(t)\cdot Fp(t) - (P_{load}(t_c) + P_{load}(t))\cdot Fp(t_c) \ge 0 \\ T > t_c > t \end{cases}, \tag{10}$$

where t_c is the next time period with regard to the current time period *t*, which is less than the maximum time slot 24 corresponding to 00:00 PM. That is one of the greatest differences between the first and the second version of the optimization algorithms. The second more improved algorithm has 1 440 time slots, instead of 24, which makes it possible to consider every minute of EES work during the day-night period. The criterion for selection of the second algorithm is presented in (11):

$$\begin{cases} Fp(t)(0) > ... > Fp(t)(d) > ... > Fp(t)(23) \\ \sum_{d=0}^{n} P_{load}(t)(d) + P_{load}(t_c)(23) \le P_{CMAX} \\ \sum_{d=0}^{n} P_{load}(t)(d) \le P_{DoD} \end{cases}, \tag{11}$$

where the first row is a sorted price series from max to min value Fp_{max} -> Fp_{min} and the second row selects for discharging only hours, the total sum of power consumption of which does not exceed DoD allowed power. The count of the discharging hours is determined by an *n* variable. To achieve correct load distribution in the array, the sort function is called, which merges the forecast prices with the 24-hour load array. The first version of the algorithm is more complicated than the second; it is required to process data in two steps. The first step takes place when the Profit Matrix (PF) function is executed. It has the main control loop with sub loops, which operates on the basis of (10). This combination allows all hours *t* to be found from the 24 h array, when discharging the battery is more profitable than using grid electricity, and charging the battery back at different hours will lead to electricity cost saving, which means a profit for consumers. When the PM is filled, the recursive function starts to search all correct hour (correct means discharging hour takes place before charging back hours) combinations *p* (1..*max*) and makes a sortable list from them. The final function sorts the list by the maximum profit value and selects the highest one. Thus, considering that one possible profit from the charging/discharging combination is as described by (11) and the maximum day profit *DayP* is as follows from (12) [1], we obtain

$$p = P_{load}(t)\cdot Fp(t) - (P_{load}(t_n) + P_{load}(t))\cdot Fp(t_n) \tag{12}$$

$$\begin{aligned} DayP = MAX(\sum_{i=1}^{i_{max}} P_i = (P_{load}(t)\cdot Fp(t) - \\ - (P_{load}(t_n) + P_{load}(t))\cdot Fp(t_n)). \end{aligned} \tag{13}$$

As we can see, another large difference between the first and the second version of the algorithm is the criterion of discharging hour selection. The first version is limited in the time slots frequency – it has only 24 slots, therefore, it considers only the entire work hour. The main key for selection of the discharging hour is a multiplication relation between the price and the load consumption P_{load}(t)·Fp(t) at that hour. The second algorithm is more flexible in terms of time slots, 1 440 in number and the major key for discharging hour selection is the price *Fp*(t). The highest price contains the hour of the highest priority it will have in the discharging queue.

V. Results

Since we had no practical results for the first version of the algorithm, we can only form an estimate of the theoretical results. To exemplify our calculation for the first algorithm, the workday of Thursday 19.11.13 was chosen. Forecasted prices were loaded from the Elering TSO web server. After processing the PM routine, the main core obtains cells with data values for searching the most profitable battery charge/discharge hour combinations with (13). Evaluation of the charge/discharge hours begins from 00 AM of East European Time. Recursion function lists the total profit from the combinations from Matrix and searches for the maximum value combination array [1]. This particular day schedule with the highest profit is: discharging batteries during 16-19, 22-23 PM and charging during 2-3 AM (14).

$$DayP = p_{1(16)} + p_{2(17)} + p_{3(18)} + p_{4(22)} = 0.04427 \text{ €} \tag{14}$$

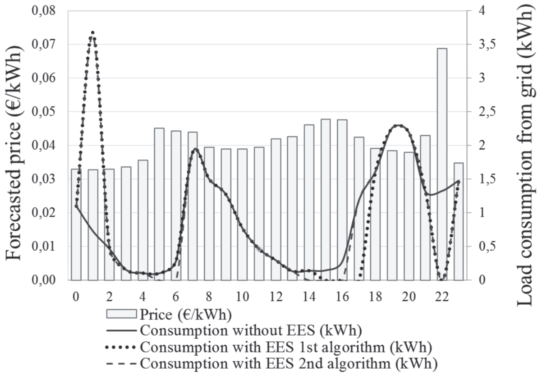

Fig. 2. Load and prices distribution with and without the use of EES and the first/second optimization algorithm for Thursday 19.11.13.

The distribution of the prices and the load curve with the use of EES and the first algorithm are presented in Fig. 2. The hours with load consumption equaling zero mean that energy for the load was taken from the batteries. Increased load curve values at other hours mean that additional load went for battery charging. The second algorithm improves the result by almost 30% (14) and the distribution of prices and the load curve with the use of EES is presented in Fig. 2.

Since the second algorithm provided better results and easier implementation, we used it for practical tests in our laboratory for a three-week period in November 2014. Some of the results obtained are shown in Fig. 3. Despite season's energy price fluctuations on the Nord Pool Spot market, we can calculate some average values and estimate forecasted results. According to the test logs, the average week's profit at EES use is *WeekP* = 0.54 €, which makes the average day profit *DayP* = 0.08 € only from the market prices. However, we should also consider energy grid taxes and fees (based on the amount of energy consumption), which will increase the price differences including *DayP* approximately three times

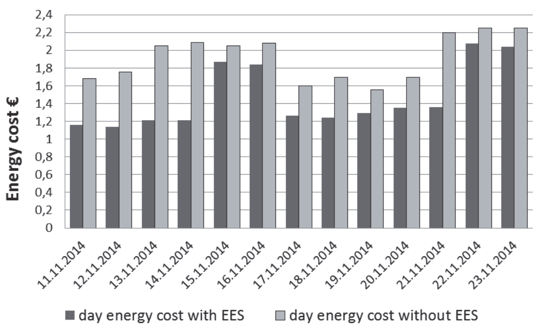

Fig. 3. Everyday energy consumption cost for a customer (in Estonia) with the use of EES and without the use of EES.

(*DayP*=0.08·3=0.24 €). The total price of the pilot system with DoD = 30% is EMS_{total} = 3 750 € (2kW, 10.6 kVAh). With reduced DoD = 14%, the total price of the pilot system is EMS_{total} = 5 200 € (2kW, 21 kVAh). Taking into account that EMS was a pilot project, its total investment price is higher than it could be in serial manufacturing. Simple calculations show that currently it is impossible to return the total cost of the EMS in its lifetime. At a certain level of energy prices and the same average day profit *DayP*, it can take 28 years to return the expenses of the EMS. In that case, we can estimate what the profit of the day use of EES should be to return an investment in the EMS in 4 years (1500 cycles), which is the usual cycle life of the Victron AGM battery with DoD in 30% [10]. If we divide the total sum of the EMS by the total days/cycles count (15), the required day profit to return the investment of the EMS is as follows:

$$DayP = EMS_{total} / 1500 = 3750 / 1500 = 2.5 \text{ €} \qquad (15)$$

If the battery DoD is 14%, the cycle life for AGM batteries [11] is approximately 4000 cycles. The EMS system cost is increased, but the demand for a day profit could be reduced at 1€.

Otherwise, the total cost of the EMS with DoD of 30% should not be higher than 360 € to match our limits in an average day profit of 0.24 € and 1500 cycles of battery life. The total cost of the EMS with the DoD of 14% should be less than 960 €. The last number could be achieved in future more easily than 360 €. The different time periods depending on the different day profit values are shown in Fig. 4. Also, we can see from the chart how the investment return time is changing with different total costs of the EMS.

VI. Conclusion

Theoretical computations illustrate that profits from the use of EES for one day are not high, even with the improved second version of the optimization algorithm; however, they can increase with a boost of load consumption or at price swing growth during the day.

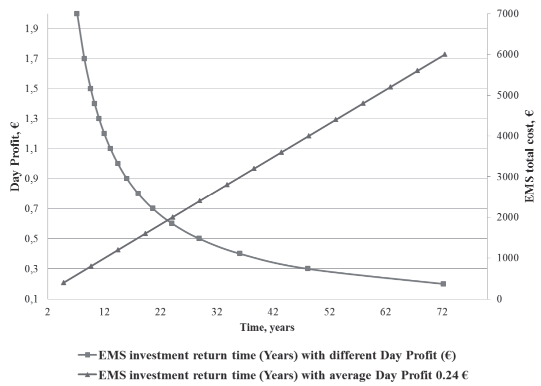

Fig. 4. Time periods for investments return depending on the day profit value and the total cost of the EMS.

Nevertheless, our everyday profit is around 0.24 € by the use of EES in the EMS. On the other hand, we take into account investments in the system and battery lifetime period, which will decrease the rationality of the system purchase. The time for investment return of the total cost (5200 €) is longer than the real lifetime of batteries. Current financial boundaries of the system require an increment of the day profit up to 1 € or a decrement of the total EMS cost under 960 €. One of the main technological improvements in the energy management system is a more flexible use of SOC of the batteries. It can be adjusted with a special variable anytime according to battery requirements. Furthermore, large amounts of time slots are used for the second algorithm, which makes the creation of the system BCDS more elastic. Major progress in research work can be achieved by fine-tuning of the current limiting values during the charge/discharge process in the Power Unit. It is still impossible on this stage of work because of the limited features in the BMV ASCII Text protocol. Also, possibilities for integration into the smart-grid systems can be explored, as both systems share some of the hardware components. This can increase the functionality of both systems at reduced initial investment costs, allowing for improved project feasibility. After system improvement and upgrade, the management algorithm will be compared with other known algorithms for energy management.

ACKNOWLEDGMENT

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Paper VII

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Simulation of Real Time Electricity Price Based Energy Management System

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Abstract—**The aim of the case study was to determine profitability of Energy Management System (EMS) in the intraday market like Elbas (Nord Pool Spot). To optimize the operation of EMS, a Demand Response (DR) algorithm was used for the calculation of a battery bank charge-discharge schedule (BCDS) taking into account the volatility in the Real-Time price (RTP). The profits are gained from importing and storing more energy at low price periods while decreasing the imported power from the grid at high price periods and dispatching the stored energy for load demands. The forecast procedure analyzes the history of the energy price for a predefined back-time period and optimizes the BCDS to bring the highest profit to the end customer. The results are composed from typical parameters of a household's energy demand applied in EMS. The results obtained were compared with those from laboratory obtained by the Day-Ahead price based control algorithm. In the tests, an one-hour price is taken as real-time price.**

Keywords—Electric energy storage; energy management system; Time Of Use energy price; Depth of Discharge; Day-Ahead prices; Real-Time prices; smart grids; price arbitrage

I. Introduction

Wholesale energy prices in the electricity market depend on the balance between energy production and energy demand. With electricity markets becoming more and more flexible, many energy providers have started to substitute the fixed retail prices schemes with dynamic prices changing during the day. Dynamic pricing, known as Real-Time Pricing (RTP), mirrors the trend movement of the wholesale market and allows reducing the volatility of the wholesale prices, also helping to reduce consumption peaks.

Electricity customers take advantage of dynamic pricing by shifting their consumption according to the Real-Time prices or by using Battery Energy Storage Systems (BESS) or Energy Management System (EMS). Storing electricity in off-peak periods allows customers to decrease electricity rates during on-peak periods [1]. It should be noted that in the energy regulation in EMS, a battery takes the main function, however, a battery's State of Charge (SOC) imposes a limitation in the algorithm since a battery cannot be freely used in extreme cases when the SOC is very high or very low [2]. Several RTP based control model implementations and descriptions can be found in different studies. An ambitious project interconnected to Demand Response (DR) area is the EU FP7 project named EcoGrid EU [6]. The aim is to develop and demonstrate a new market concept with five- minute resolution, where residential and commercial customers are responsive to imbalance pricing close to operation.

A good approach with dynamic optimization is proposed in [7]; however, storage devices much bigger than ordinary household's storages are used. Another multi-period energy with reserve pre-dispatch model and energy re-dispatch model for real time operation were studied in [8]. The idea to use Home Energy Management Scheduler (HEMS) with three subsequent phases: real-time monitoring (RTM), stochastic scheduling (STC), and real-time control (RTC) is addressed in [9]. However, the target there is to find an optimal way of scheduling household appliances to minimize the cost of energy consumption. In this system, no prior function is attributed to battery storage. Other studies [10] and [11] also focus on algorithm development. In [10], the function of an electrical vehicle in the BESS is discussed. According to [11], in case of multiple energy providers in the system, the customers need to determine both the optimal energy consumption allocation at each hour and the optimal energy provider for each customer. In addition, load scheduling optimization pseudo code in [12] imposes restrictions in household's application due to the photovoltaic energy source, which is not obtainable at any time.

The work presented here was motivated by the results of previous research where an algorithm intended for Day-Ahead prices in the Nord Pool Spot market was improved for use in EMS [4]. Practical results from the use of EMS and BESS obtained failed to show satisfactory savings, however provided motivation for further improvement.

Here a RTP energy market is addressed to develop a new Real-Time price based control algorithm for EMS. As compared to the algorithm in [4], which uses known electricity prices for the next 24 hours, our new algorithm has an advantage of flexible functionality of the BCDS during unclear stochastic price movement at only one-hour time period. It is an important feature for providing regulating service in the electricity market. In the algorithm, only the price forecast data and price history are considered along with a household's energy consumption. This work contributes to testing the proposed RTP algorithm in real conditions of EMS,

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since growing usage of renewable energy sources leads electricity markets to transit to one-hour time resolution. It is based on a simulation system of household energy demand with a battery bank on board. The results of comparison between the previously studied Day-Ahead algorithm (DAA) and the proposed RTP algorithm are presented. The aim is to show a possible profit or loss for customers whenever they decide to participate in Day-Ahead or Real-Time price electricity market by using the same EMS.

II. Constraints For RTP Based Control Algorithm

In this paper initial parameters similar to those in the DAA approach in [4] are used. Thus, it is easy to compare the results in the study of profits earned by the DAA or the new RTP algorithm:

- Maximum Depth of Discharge (DoD) per BCDS cycle is 35%;
- SOC=100% of battery bank equals 21 kWh;
- Maximum load consumption per hour is 1.5 kWh;
- Battery charging current is limited at 15 A.

The RTP algorithm of EMS considers the revenue that could be achieved only through energy price arbitrage, i.e. taking advantage of price differentials in the wholesale electricity market with the BESS. That kind of trading is suitable for the Nord Pool Spot intraday market Elbas. It is a continuous market where power trading takes place until one hour before the power is delivered. Trading members can adjust their power production or consumption plans close to delivery [5]. Time frames of the Nord Pool Spot market are shown in Fig.1. The intraday energy market means higher participation of customers and loads in the power system. It is more complicated to forecast the price and to control or shift load consumption in these systems.

The main features of the previous DAA [4] are: use of next 24 h prices of the EMS system and ability to achieve the maximum welfare from prices arbitrage and BESS usage. It means one battery charge-discharge cycle per each day.

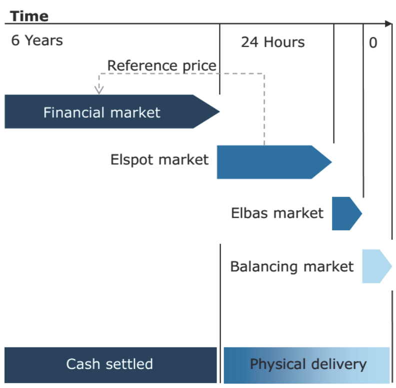

Fig. 1. Nord Pool Spot markets: Elspot and Elbas.

From the practical trial of the DAA, an average day profit of 0.11 € during ten days of November 2014 was derived [4]. Although the day profit figure differs essentially from the investment return value at 2.5 €, it enables comparison of the algorithms. In the EMS, profit per day is the main score rate parameter, but the RTP algorithm may to provide a battery charge discharge cycle every day. The conditions for charging or discharging of BESS depend on the current hour price, price history and SOC (1):

$$SOC(t) = SOC(t-1) + x_1 \cdot \eta \cdot P_C(t) - x_2 \cdot P_D(t), \qquad (1)$$

where $P_C(t)$ is the charging power; $P_D(t)$ is the discharging power; $SOC(t)$ is the state of charge at the end of period t; $SOC(t-1)$ is the state of charge at the end of period $t-1$; η is the charging efficiency; x_1 and x_2 are charge/discharge state variables. All the variables must be within their operation limits, expressed as in (2):

$$\begin{cases} 0 \le P_C(t) \le P_C \max \\ 0 \le P_D(t) \le P_D \max \\ SOC\min \le SOC(t) \le SOC\max \\ \text{charging}: x_1 = 1, x_2 = 0 \\ \text{discharging}: x_1 = 0, x_2 = 1 \end{cases} \qquad (2)$$

where $SOCmin$ is the minimum value of the state of charge; $SOCmax$ is the maximum value of the state of charge; P_Cmax is the maximum value of charging power; P_Dmax is the maximum value of discharging power.

The scheduling process for the RTP algorithm runs continuously for every new hour, undivided into 24 h periods like with the DAA. This means that in some periods or days, BESS may only charge, discharge or be in idle state (load is fed directly from the grid). On the other hand, to simplify the comparison, average day profit is calculated from the total profit achieved by all days of the simulation. The most informative description of the new RTP algorithm is its profit or loss, as compared to regular (without EMS) household energy use. Regular energy consumption cost for a time period T can be described by (3). The time period consists of timeslots t with $t = 1 \ldots T$, where a minimum time unit is 1 hour:

$$C_{tot} = \sum_{t=1}^{T} (P_{grid}(t) \cdot F(t)), \qquad (3)$$

where C_{tot} is the total cost of energy for a particular time period; P_{grid} is power from the grid to cover load consumption; $F(t)$ is electricity price, ¢/kWh of the current hour. To simplify calculations, load power P_{load} is assumed equal to grid power. The idea of the new RTP algorithm is to minimize the cost of energy by using EMS. It is valid if the condition (4) is true and (5) shows profitability of the algorithm in EMS:

$$C_{alg} < C_{tot}, \qquad (4)$$

$$\alpha = \frac{100\cdot(C_{tot} - C_{a\lg})}{C_{tot}}, \tag{5}$$

where C_{alg} is the total cost of energy by using the algorithm for a particular time period; α is relative reduction of the energy cost.

III. Design of RTP Based Control Algorithm

The core of the RTP algorithm is the prediction logic of optimized price levels. Since only the current price for the next hour is available, and the prices for future periods of time are unknown, it is important to use tuned parameters and price history to forecast market's trend behavior and find out the most profitable time-slot (hour) for charging or discharging of BESS. The system analyzes *n* day history of hourly prices. The developed algorithm finds minimum and maximum prices (local extremes) for each day in a described time range. These local extremes are used to calculate minimum level $L_{min}(t)$ price and maximum level $L_{max}(t)$ price for the current hour. To avoid rapid change of stated levels, the values are smoothed by simply moving the average (SMA) function. To enhance the probability that the price of the beginning hour will reach and cross either L_{min} or L_{max}, also minimum level is increased by margin H_{min} (6) and maximum level is decreased by margin H_{max} (7):

$$L_{\min}(t) = \frac{\sum_{i=1}^{n} F_{\min}(t-i)}{n} + H_{\min}, \tag{6}$$

$$L_{\max}(t) = \frac{\sum_{i=1}^{n} F_{\max}(t-i)}{n} - H_{\max}, \tag{7}$$

where F_{min} is the array of daily minimum price and F_{max} is the array of daily maximum price of *n* days. The flexibility of the algorithm allows optimization of the parameters *n*, H_{min} and H_{max} to achieve maximum profit of the system. In this study, parameters are based on the loop optimization as follows:

- SMA period $n = 2$ days for minimum price array;
- SMA period $n = 6$ days for maximum price array;
- minimum level margin $H_{min} = 0.2$ ¢;
- maximum level margin $H_{max} = 1.6$ ¢.

The diagram of the core logic of the algorithm is shown in Fig. 2 and the behavior of the real system is shown in Fig. 3. When the current hour electricity price *F(t)* crosses below the minimum price level $L_{min}(t)$, the charging mode of EMS is activated, and when *F(t)* crosses above the maximum price level $L_{max}(t)$, the discharging mode is activated. Also, the algorithm controls the SOC limits and has idle state (8):

$$\begin{cases} F(t) \geq L_{\max}(t) \wedge SOC(t) > SOC\min \rightarrow x_1 = 0, x_2 = 1 \\ F(t) \leq L_{\min}(t) \wedge SOC(t) < SOC\max \rightarrow x_1 = 1, x_2 = 0, \\ F(t) > L_{\min}(t) \wedge F(t) < L_{\max}(t) \rightarrow x_1 = 0, x_2 = 0 \end{cases} \tag{8}$$

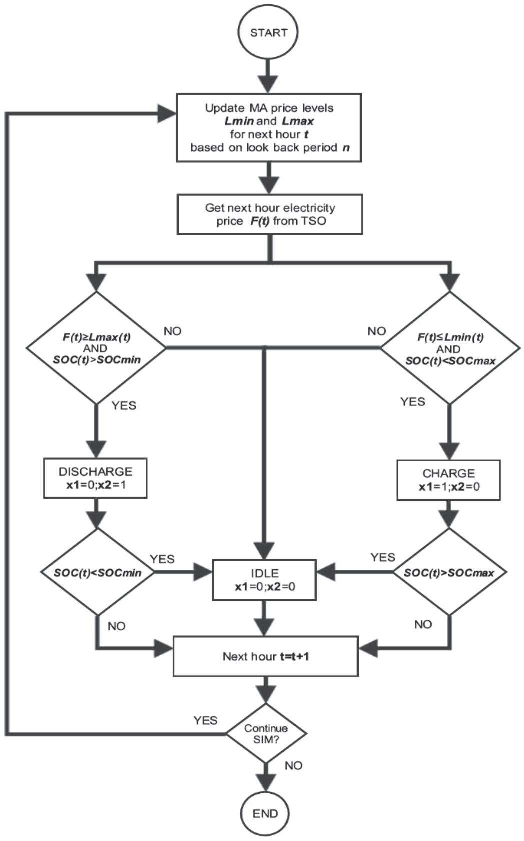

Fig. 2. Diagram of the RTP algorithm core.

The total cost of energy for a particular time period will be calculated as follows (9):

$$C_{a\lg} = \sum_{t=1}^{T} (P_{load}(t)\cdot F(t) - (P_{load}(t)\cdot F(t)\cdot x_2) + \\ + (P_C(t)\cdot F(t)\cdot x_1)) \tag{9}$$

The result of the total energy cost can be used with (7) – (9) in a simple loop or Monte-Carlo optimization. The aim of the optimization is to find out parameters L_{min}, L_{max}, H_{min} and H_{max}, which will provide the maximum profit *Pr* according to (10):

$$\Pr = MAX\ (\sum_{t=1}^{T} (C_{tot} - C_{a\lg})), \tag{10}$$

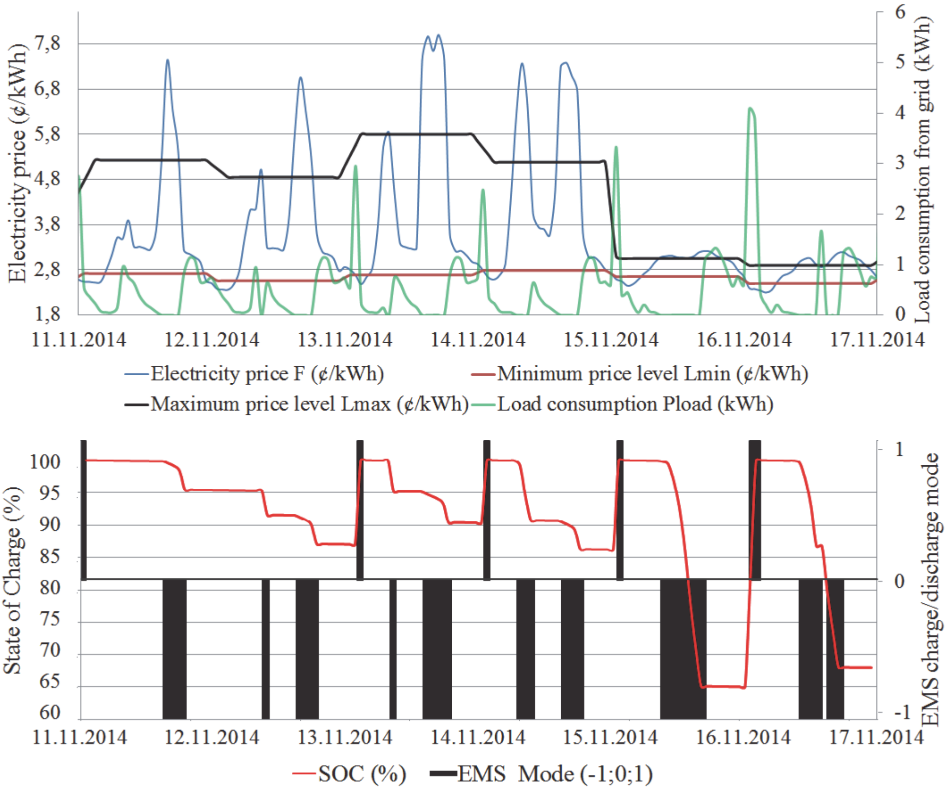

Fig. 3. Load, prices and battery mode distribution in EMS for the period from 11.11.14 to 17.11.14.

IV. Results of Simulation

The algorithm performance was tested with a simplified constant load array during a 24 h period, with difference in load values set for a weekday or for a weekend. It means that the load is not shifted in the EMS system and comfort level for customer remains unchanged.

The EMS storage consists of a battery pack with deep cycle AGM batteries 12VDC having a total capacity of 440 Ah in pairs, making a total voltage of 24V, capacity of 880Ah, amounting to a total stored energy of 21 kWh. This capacity was selected with a particular Depth of Discharge (DoD) to cover simulated household's load demands. EMS components are described in [3].

The algorithm analyzed was tested theoretically during the same historical period as the DAA in [4]. Different algorithms are compared in Table 1.

According to (4), total costs of the DAA and the RTP algorithm for a week period are less than the cost of energy without EMS, thus they are potentially feasible. The day profit (*DayP*) result obtained with the new RTP algorithm is 6.6 ¢ (€ cents). Considering the prices with distribution grid taxes and fees (based on the amount of energy consumption) will increase the RTP profit per day approximately three times *DayP* = 6.6 x 3 = 19.8 ¢. Still this result is lower than required *DayP* = 1 €, found in [4]. Thus, the day profit of the RTP makes the return of investment for EMS impossible.

TABLE I. Energy Cost with Different Algorithms

Date	**Results of Algorithms**		
	No EMS, cost (¢)	***DAA, cost (¢)***	***RTP, cost (¢)***
11.11.14	35.3	23.3	30.2
12.11.14	37.1	30.3	28.4
13.11.14	41.5	31.5	35.7
14.11.14	44.1	32.3	30.6
15.11.14	50.0	49.7	35.5
16.11.14	48.6	46.8	46.1
17.11.14	40.7	29.7	44.8
Total	297.3	243.5	251.3
Day's average	42.5	34.8	35.9
Day's profit	0.0	7.73	6.6

With regard to the results of RTP and previous DAA [4], according to (5), DAA profit per day is equal to 25.1% and RTP algorithm profit per day is equal to 15.5% in case costs of energy for household consumption are compared without BESS. It is evident that the optimized RTP algorithm is of 10 percent point lower profitability than DAA.

V. Conclusion

Our calculations have illustrated that using the RTP algorithm, the profit is 10 percent point lower than with the DAA algorithm considered in [4]. It gives an average day profit of 19.8 ¢, which is less than the required 1 € day profit. It means that investments into EMS with the RTP algorithm cannot be returned during the life time of a battery bank. However, the use of EMS provides other benefits, such as increased supply reliability, ability to combine electric system with other renewable energy sources and simpler implementation of household's network into a smart grid, if needed. These factors drive further research and development of EMS.

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Paper VIII

Auväärt, A.; Rosin, A.; Belonogova, N.; **Lebedev, D.** (2011). Nord Pool Spot price pattern analysis for households energy management. *In: 7th International Conference-Workshop Compatibility and Power Electronics (CPE2011), Tallinn, Estonia, June 01-03, 2011:* IEEE, 2011, 103 - 106.

NordPoolSpot price pattern analysis for households energy management

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Abstract - This paper describes the analysis of price fluctuations in the Nord Pool Spot (NPS) and the possibilities to introduce consumption scheduling and energy storage equipment to reduce price fluctuations in households using the real-time open market electrical energy tariffs.

I. INTRODUCTION

The deregulation of electricity industry is giving way to global trends toward the commodization of electric energy. [1,2]. This trend has intensified in Europe and North America, where market forces have pushed legislators to begin removing artificial barriers that have shielded electric utilities from competition. The price of electricity is far more volatile than that of other commodities normally noted for extreme volatility. Relatively small changes in load or generation can cause large changes in price and all in a matter of hours. Unlike in the financial markets, electricity is traded every hour of the year - including nights, weekends and holidays. Unlike other commodities, electricity cannot be stored efficiently. Therefore, delicate balance must be maintained between generation and consumption 8760 hours a year.

There is, however, a great difference between electricity and the other energy (and commodity) markets in that the variable costs of production vary so greatly between different types of installation – Wind and Hydropower with a virtual nil cost at one extreme and Gas Turbines at the other end of the scale. In order to satisfy fluctuating consumer demand at the lowest cost, a broad variety of generating techniques are required. Some installations are capital intensive but can be run year round and are relatively fuel efficient (hydro, nuclear, coal-fired). Other units such as co-production of heat and power are used less frequently to cover winter heating demand at times of higher prices. Whilst energy intensive units such as Gas Fired Turbines are used for brief periods of very high price and demand.

Although the principle of generation electricity is simple, generating electricity for an area as large as Europe, means a complex balancing process. One of the biggest problems faced by the system operator is congestion. When congestion occurs, zonal prices supersede power exchange's market clearing price, which is based on the aggregated energy supply and demand curve intersection point for each hour [5]. In such a case, electricity prices can increase or decrease dramatically. The primary role of a market price is to establish equilibrium between supply and demand. This task is especially important in the power markets because of the inability to store electricity efficiently and the high costs associated with any supply failure. NPS runs the largest market for electrical energy in the world, offering both day-ahead and intraday markets to its participants. 330 companies from 20 countries trade on the Exchange. In 2009 the NPS group had a turnover of 288TWh [7]. The spot market at NPS is an auction based exchange for the trading of prompt physically delivered electricity. The spot market carries out the key task of balancing supply and demand in the power market with a certain scope for forward planning. In addition to this, there is a final balancing process for fine adjustments in the real time balancing market. The spot market receives bids and offers from producers and consumers alike and calculates an hourly price which balances these opposing sides. NPS publishes a spot price for each hour of the coming day in order to synthetically balance supply and demand. Every morning Nord Pool participants post their orders to the auction for the coming day. Each order specifies the volume in MWh/h that a participant is willing to buy or sell at specific price levels (€/MWh) for each individual hour in the following day. The SESAM (Elspot trading system) calculation equation (1) is based on an application of the social welfare criteria in combination with market rules. SESAM is maximizing the value of the objective function subject to physical constraints; like volume constraints, area balances, transmission and ramping constraints.

$$Max\sum_{n}\left\{\int_{0}^{d^a} D^a(x)dx - \int_{0}^{s^a} S^a(y)dy\right. \quad , \qquad (1)$$

where a represents an area, d^a is the demand in the area a and D^a is the demand function in the area a, s^a is supply in the area a, S^a is the supply function in the area a, and n is the number of areas. The system price (SP1) for each hour is determined by the intersection of the aggregate supply and demand curves which are representing all bids and offers for the entire Nordic region [7]. In addition to area price there is also an annual fixed fee and a variable trading fee for all market participants.

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In the political debate surrounding energy, this type of price formation is labeled a marginal price setting. This gives a false impression that the establishment of prices in the electricity market is different from the price formation process in other commodity markets. The only difference lies in the significantly higher requirements for the secure delivery of electricity because it must be delivered at the precise moment it is needed by the consumer. The inelasticity caused by the inability to store electricity is the reason of this difference.

II. AVERAGE DAILY PRICE

To find the possibilities to use the possible fluctuations we constructed an average day from actual data from the NPS trading system. We studied a period of seven months starting in April 2010. An average was calculated with the well-known formula of a generalized mean

$$\bar{x} = \sqrt[m]{\frac{\sum_{i=1}^{n} x_i^m}{n}}, \qquad (2)$$

where X_i is the price of electrical energy in the instance i

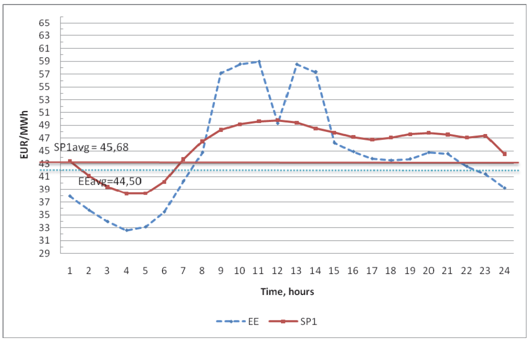

Fig. 1 Average daily price at the EE area and SP1 area

Equation (2) is used to calculate the average price during the period in the EE area. It is calculated as 44.500€/MWh. One hour is the smallest time interval when prices can change, because on spot electricity trading prices are set constant for delivery of power during a certain hour. The chart in Fig. 1 compares an arithmetic average price during the day in the NPS SP1 area and EE area. It shows very clearly that fluctuations in the system area are small - around 11.00€/MWh, but in the EE area the amplitude of the price during the day is much higher at 26.35€/MWh. The high price amplitude in the local market provides opportunities to use consumption scheduling models in residential areas to gain economy.

We can also observe differences on workdays and at weekends in figures 2 and 3

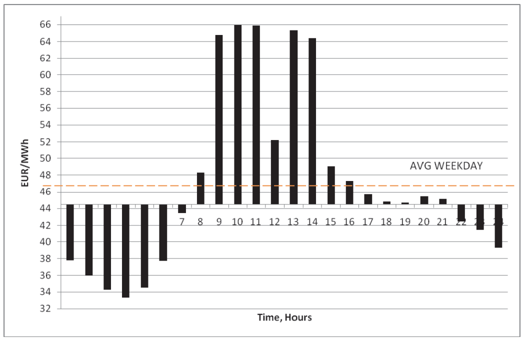

Fig. 2 Average daily price on workdays in the EE area

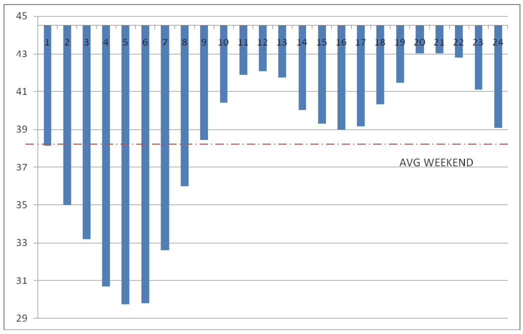

Fig. 3 Average daily price at weekends in the EE area

The price curve is not similar on workdays and at weekends. The maximum price on workdays is 65.93€/MWh and the minimum is 33.35€/MWh. At weekends the maximum and minimum prices are 43.05€/MWh and 29.76€/MWh,

Average price below the EE area average (44.500€/MWh) is 38.02€/MWh (-14.55%) on workdays and 38.256€/MWh (-14.03%) at weekends. Average price above the EE area average is 53.496 €/MWh (20.22%) on workdays and does not exceed the average at weekends.

III. AVERAGE PRICE DEVIATION

Fig. 4 shows the deviation calculated by the simple formula (3) from the average price to analyze possibilities to use off-peak hours to store energy or shift the load to off-peak hours. We needed an assurance of off-peak hours available to recharge the batteries or other storage equipment. We found that the average duration of peaks that are higher than the average area price is 9.59 hours and the average duration of off-peaks is 13.48 hours. That means there is plenty of time to recharge storage equipment during the off-peak time.

Deviation from an average price is higher at peak hours, but peak hours last less than off-peak hours. It is most profitable to save energy between the 23...06 o'clock, then the price is lower than 10% compared to average. There is also a possibility to save energy between 16...19 o'clock when the price is about 2-3% lower than average.

$$S = \frac{\sum_{n=1}^{k} \frac{x_i}{n} - X_F}{X_F}, \qquad (3)$$

where X_i is the price of electrical energy in the instance i (from 0-24 hours) and X_F is the average area price.

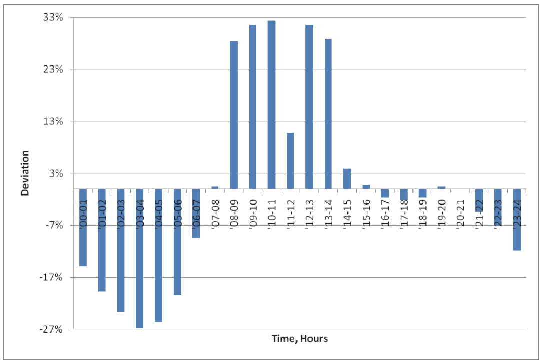

Fig. 4 Average EE area price deviation

Another feature of volatility of electricity price is its seasonal character. The daily and weekly seasonality can be illustrated by intra weekly plot of mean absolute hourly price changes (Fig. 5). The patterns of volatility are clearly correlated to the on-peak/off-peak specification of the market. The lowest volatility is observed at the weekends and during night. The huge increase of price within hours 33-39 is a result of emergency shutdown of the thermal power plant section in the EE area. For electricity spot price returns there is strong 7-day dependence. It is surprising that this dependence lasts almost forever [4].

Another seasonal phenomenon is observed on yearly basis as we compare NPS SP1 prices in 2009 the price is much higher on the winter season but remains nearly the same in other seasons as plotted in Fig. 6. The price curve in summertime for the EE area in 2010 is quite similar to trends observed in the SP1 area on summertime.

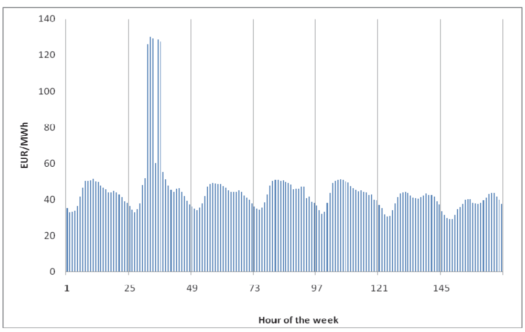

Fig. 5 Intra-weekly plot of mean absolute hourly EE area price changes for the NPS market. The statistical week is divided into 168 hours from Monday 0:00 to Sunday 24

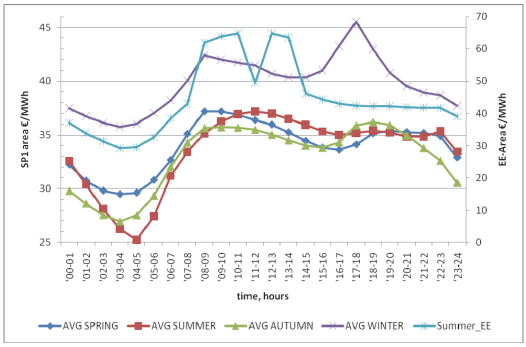

Fig. 6 Average daily price at the SP1 area on the seasonal scale compared to the EE price at summertime

IV. DISTRIBUTION OF PRICE RANGE

As seen in Fig. 7 the distribution of prices is symmetric and leptokurtic. With the leptokurtic distribution, the price will have a relatively low amount of variance, because return values are close to the mean. This could mean that energy producers will not try to invest to storage facilities as there could be quite small return on investment. This gives us an opportunity to continue our research on the profitability of using energy storing and shifting on the demand side.

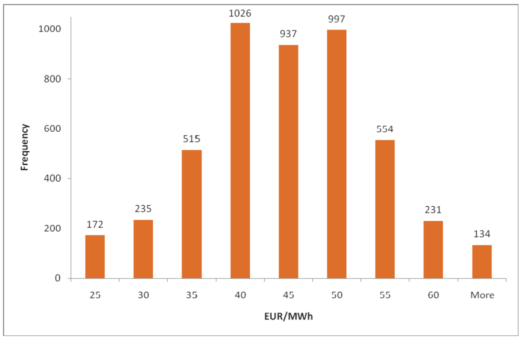

Fig. 7 Distribution of price range in the EE area

V. HOUSEHOLD ENERGY CONSUMPTION COMPARED TO AVERAGE PRICE DEVIATION

Energy consumption in households in the UK is reported in [8] and in Estonia in [3]. Peak hours for UK households form 06-08 and 13-18. Main peak hours for Estonian average households are at 7-8 and 19-21 on workdays and 12-14 and 19-21 at weekends. It is quite easy to see the possible use of energy storage to smoothen the loads at morning or midday use and even the evening use at weekends. However, some exact calculations are needed in terms of the possibilities to conserve energy at low price before evening peak hours on working days.

VI. POTENTIAL OF ENERGY STORAGES IN HOUSEHOLDS

NPS prices have been already implemented for large industrial customers in Finland. Spot market prices open opportunities also for demand response, i.e. load control for small customers. Moreover, price demand response has been already tested in Finland on residential customers and has revealed the benefits for energy costs optimization [9].

In future, energy storages will help reduce price fluctuations in spot market if used smartly. Storages can be classified into heating and electrical ones. In heating storage energy is charged and discharged in form of heating, while in electrical energy storage – in form of electricity. Electrical energy storage can be stationary (batteries) or mobile (electric vehicles). Heating energy storage represents water and/or space heater in residential houses with electrical heating loads. Although this kind of energy storage is already available in many households, as well as it has rather high energy density compared to other household appliances and therefore could have a significant impact on market prices if adjusted to them, it is less flexible in time because its usage is limited by customer's comfort requirements.

The usage of electrical energy storage is, on the contrary, less dependent on customer's requirements, but on market prices. It is in customer's interests to use (discharge) energy storage in high price hours and charge it in low price hours. The recent research shows that technical profitability of peak power reduction using energy storages is limited to 30% of network penetration [10]. Optimization of electrical energy storage charging/discharging cycles according to market prices is an important further research question. The main objective of customers is to minimize their energy costs. At the same time, they contribute to leveling peak powers in the network and to reducing the volatility of spot prices in the market. That way, residential customers can contribute to their own welfare and welfare of other market players, since the price risk of energy supplier will be minimized due to stable market prices as well as both distribution company and customer will benefit from good quality of electricity supply.

VII. CONCLUSION

This paper analyzes the fluctuations of electrical energy price in the NPS EE price area and to some extent in the SP1 area. The NPS area is currently the largest free electricity market today with a turnover of 277TWh/year. Our analysis shows that energy price in the open market is far more volatile than other commodities, but it does not behave like most financial instruments as it has a strong seasonal character.

There is a possibility to use renewable energy for local production of electricity during peak times. Solar and wind power generation would be most suitable for households.

The most perspective type could be solar power as it is usable at high peak times during the day, but the main problem in the NPS area is winter period when the effectiveness of photovoltaic panels decreases. Another possibility is to use wind power but this source is far less reliable than the sun and could not be generated without opposition from inhabitants in densely populated areas.

We observed the EE area price during 4802 hours starting from 1 April 2010 when Estonia entered the NPS market. During that time an average hourly price for the EE price area was 44.5€/MWh and it is slightly lower than the price in the system area. The price curve is similar on weekdays and at weekends. At weekends the average hourly price remains under an average area price during the observation time.

The price will always be lower than average at off-peak times. An average off-peak time lasts for 13.48 hours, which is long enough to store energy with cheaper storage equipment or shift the power usage to a less expensive time period without losing customer's comfort requirement.

Some economic impact on consumers who will buy their electricity from the open market could occur. As the prices for next day are known at least 12 hours in advance, the complex prediction models for scheduling or storing energy are not necessary. It is quite clear that until the electrical energy producers will not use energy saving technologies, the price will fluctuate almost in the same way as described in this paper. Additionally, some questions remain about changes in the behavior of prices when the households or other micro grids join the NPS market.

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