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PERSPECTIVES OF CONTROL THEORY IN SMART GRIDS: ARTIFICIAL INTELLIGENCE, OPTIMIZATION, AND HUMAN BEHAVIOR

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SMART GRID DEFINITIONS

A **smart grid** is an electrical grid, which includes a variety of operation and energy measures including smart meters, smart appliances, renewable energy resources, and energy efficient resources.

… a reliable and secure electricity infrastructure that can meet future demand growth and to achieve each of the following…:

(1) … digital information and **controls** technology …
(2) dynamic **optimization** of grid operations …
(3) …distributed generation and renewables
(4) …demand response … and energy efficiency…
(5) …'smart' technologies for metering, communications
(6) … 'smart' appliances and consumer devices
(7) … electricity storage and peak-shaving technologies
(8) … timely information and **control** options to customers
(9) …standards for communication and

… an electricity network that can cost efficiently integrate the behavior and actions of all users … to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety. Employs innovative products and services together with intelligent **monitoring, control, communication, and self-healing technologies** …

- … operation of generators of all sizes and types
- … consumers play a part in optimizing operation
- … greater information for consumers and options for how they use their supply
- … reduce environmental impact…
- … system reliability, quality and security

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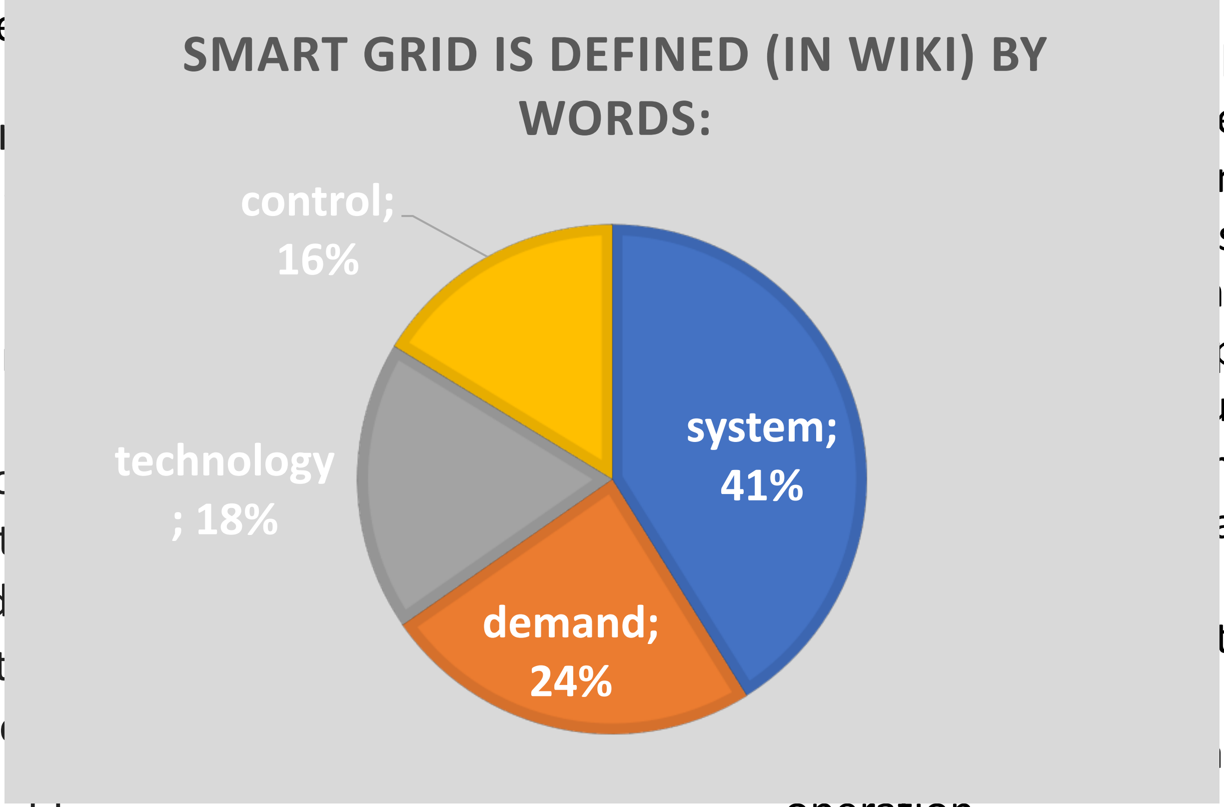

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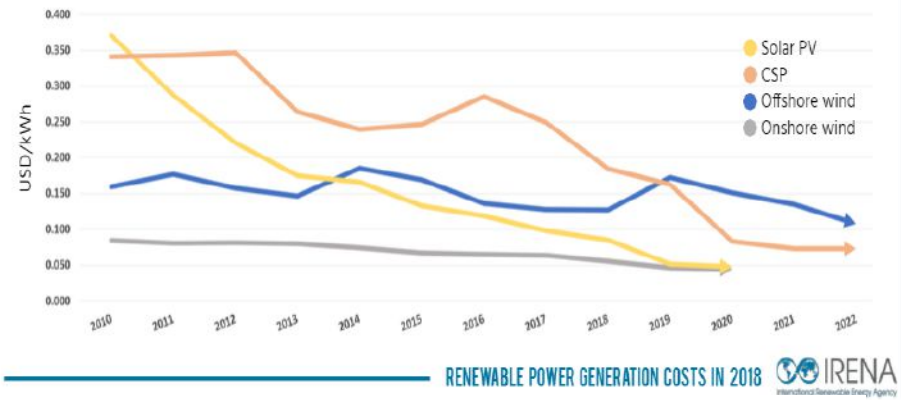
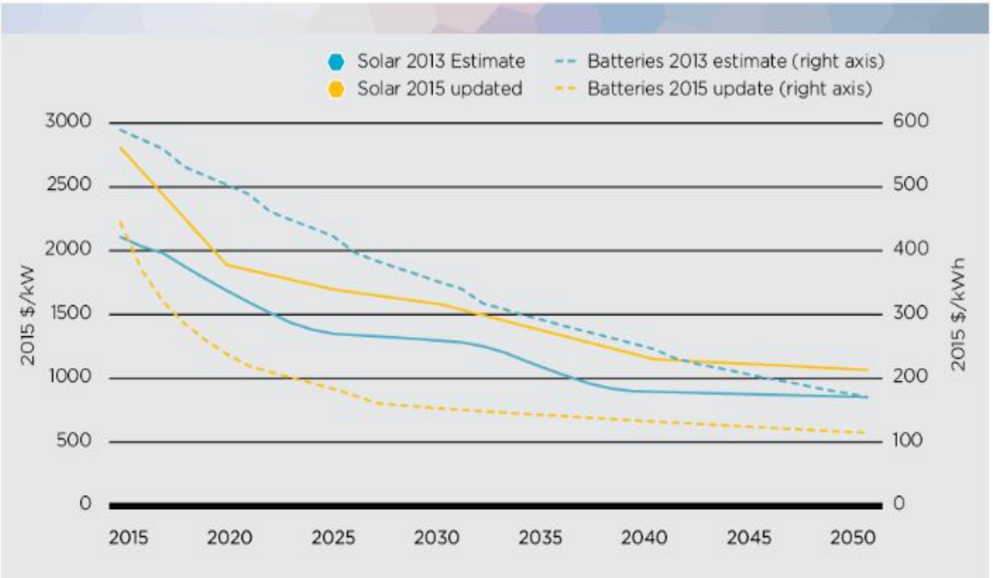
“SMART” (MacMillan Dictionary)

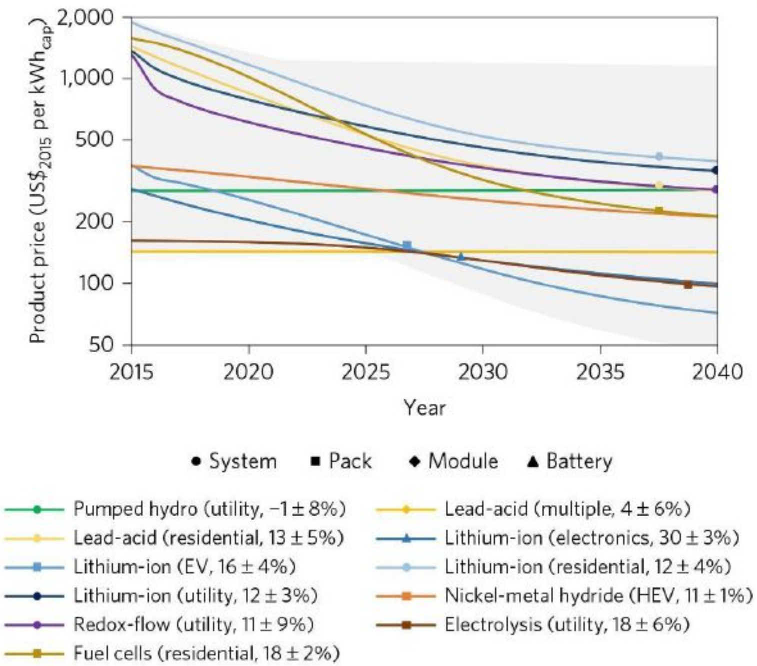
1. clean and neat in appearance and dressed in nice fashionable clothes, especially in a slightly formal way
2. intelligent
3. speaking or behaving in a clever or funny way that shows a lack of respect
4. connected with rich fashionable people
5. a smart movement is quick and full of force or energy
6. smart machines, especially weapons, use computer technology to make them effective

CHALLENGES IN RENEWABLES AND STORAGE

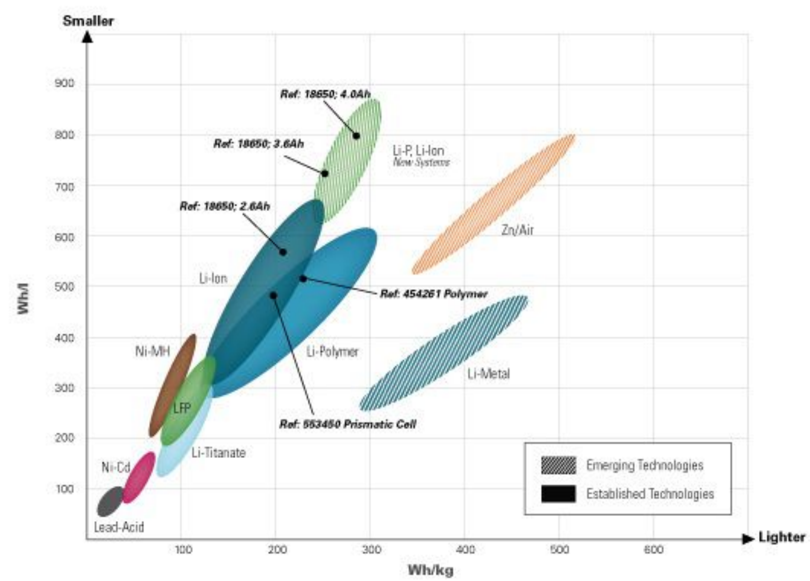
By 2020, **onshore wind** and **solar PV** will be a less expensive source of new electricity than the cheapest fossil fuel alternative.







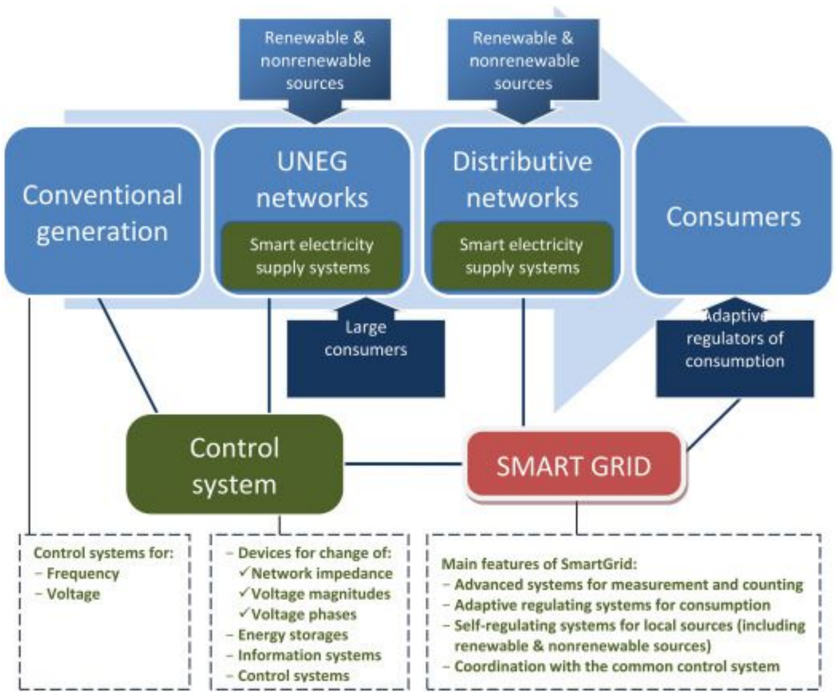
Comparison of Energy Densities for Various Battery Chemistries

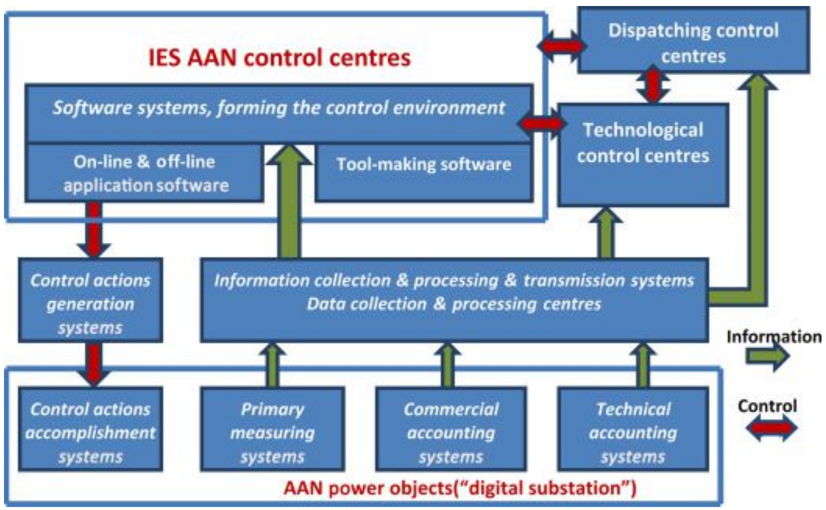


RUSSIAN SMART GRID: INTELLIGENT ENERGY SYSTEM WITH ACTIVE AND ADAPTIVE NETWORK

Intelligent electric power system with active and adaptive network (IESAAN) is a new generation of energy systems based on the **multi-agent operation control** and **development management** technology aimed at efficient use of all kinds of resources (natural, social, human, or production) for reliable, high-quality and efficient energy supply as a result of the flexible interaction of all its subjects (all types of generation, networks, and consumers) by virtue of modern equipment and an **integrated hierarchical intelligent control system**.

(From the framework of IES AAS, 2011)



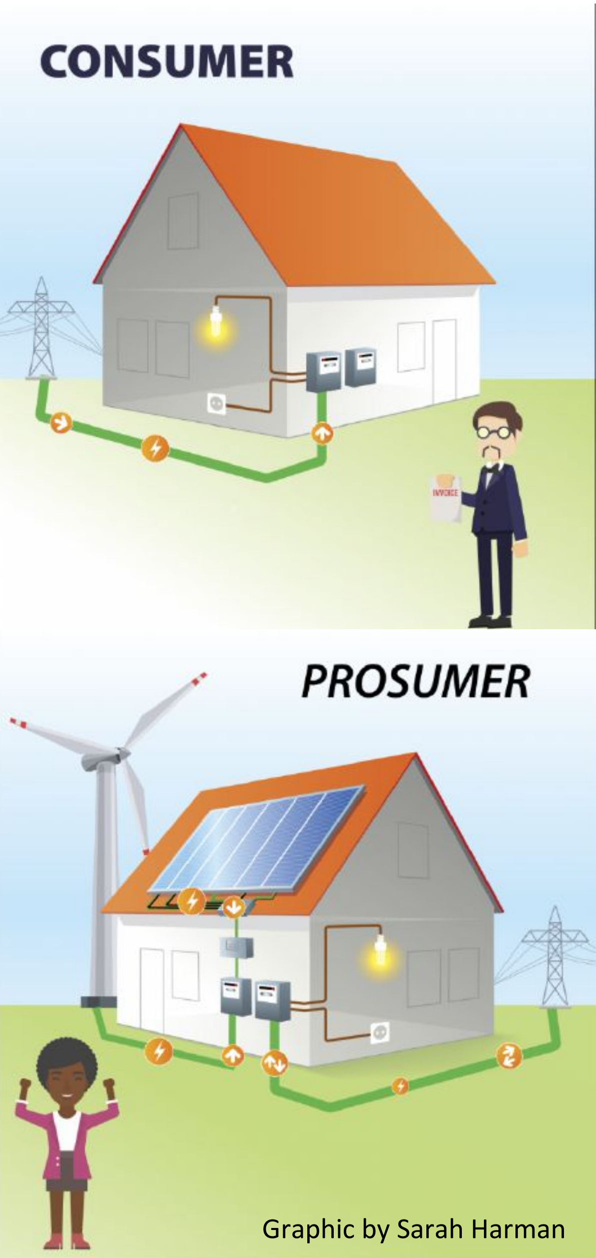


ACTIVE CONSUMER

An **active consumer is** a participant of the retail electricity market that may choose her own load and/or generation to achieve her goals (minimize electricity bill or to maximize the profit from selling electricity or capacity).

An active consumer may choose:

- the workload of her electric equipment and appliances implementing production plans or feeding her household to minimize the electricity bill
- Degree of involvement into the provision of additional services (direct active/reactive load control)
- distributed generation schedule to sell electricity to the retail and to the wholesale electricity market)



MATHEMATICAL MODEL OF ACTIVE CONSUMER

The cost function is “operational” cost

$$C(\boldsymbol{d}(\theta,\eta),\boldsymbol{a},\boldsymbol{s},\boldsymbol{g},\boldsymbol{r},\theta,\xi,\eta)$$
$$=\sum_{t=1}^{T} p_a(t,\boldsymbol{n},\xi_a,\eta)ReLU(n\ (t)) - \sum_{t=1}^{T} p_g(t,-\boldsymbol{n},\xi_g,\eta\ )ReLU(-n(t))$$
$$+\sum_{t=1}^{T} C_{ga}(t,g(t),g(t-1),\theta,\eta) + \sum_{t=1}^{T} C_g(t,g(t),\theta,\eta) + C_{da}(\boldsymbol{d}(\theta,\eta),\boldsymbol{a},\theta,\eta)$$

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where t = 1, …, T – operation periods

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$r(t)$ – battery discharge volume in period t, **r** – battery discharge profile

n = **a** + **s** – **g** – **r** – net consumption profile

$\xi = (\xi_a, \xi_g)$ – parameters of the tariff rule for consumed/regenerated e

η – environment parameters at the planning horizon

θ – the “type” of the consumer (the list of characteristics that affect tl

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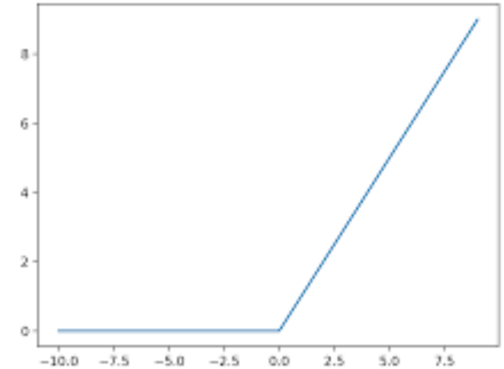
***C_{da}*(d, a, θ, η), – demand response costs on the planning horizon**



LOAD PREDICTION FROM AGENT-BASED MODELS

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$$C(\boldsymbol{d}(\theta,\eta),\boldsymbol{a},\boldsymbol{s},\boldsymbol{g},\boldsymbol{r},\theta,\xi,\eta) = \sum_{t=1}^{T} p_a(t,\boldsymbol{n},\xi_a,\eta) ReLU(n\,(t)) - \sum_{t=1}^{T} p_g(t,-\boldsymbol{n},\xi_g,\eta\,) ReLU(-n(t)) + \sum_{t=1}^{T} C_{ga}(t,g(t),g(t-1),\theta,\eta) + \sum_{t=1}^{T} C_g(t,g(t),\theta,\eta) + C_{da}(\boldsymbol{d}(\theta,\eta),\boldsymbol{a},\theta,\eta)$$

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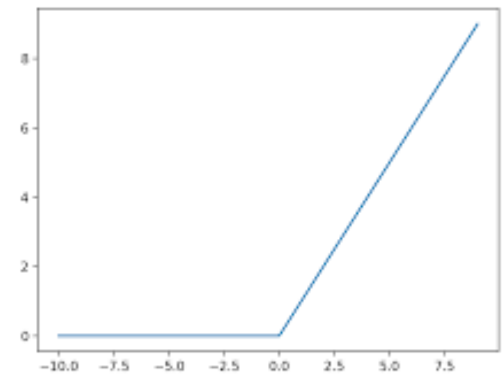
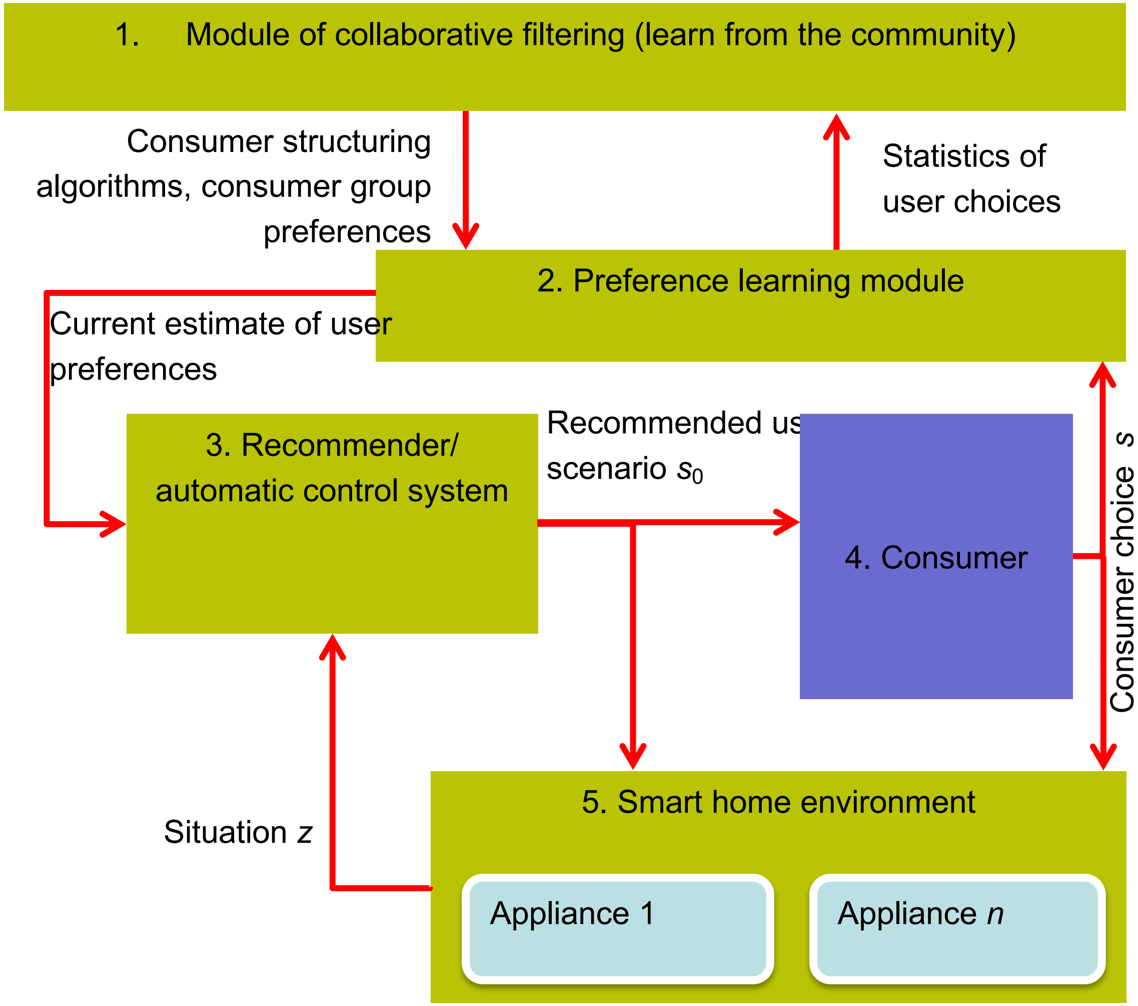
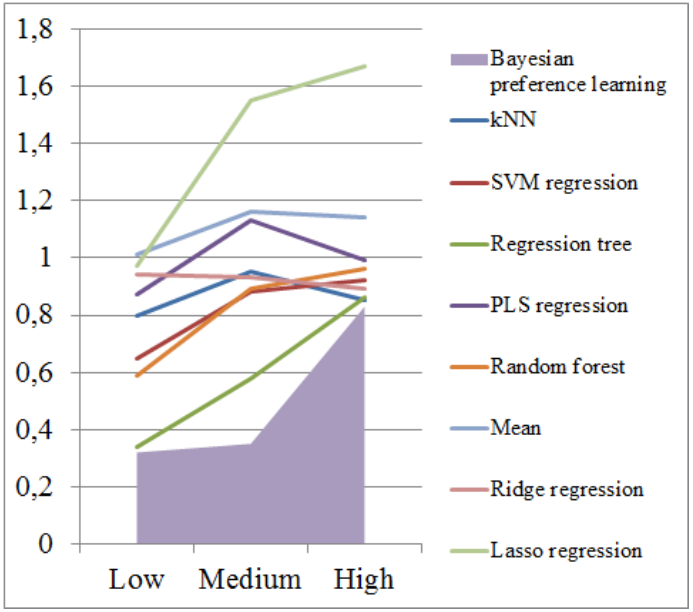


- User hate silly surveys about their plans and preferences
- Smart home environment must learn preferences and plans from user actions and the history of appliance use
- An example is a “smart thermostat” Nest, which elicits relations between external conditions and user actions and adapts the rules
- However, this approach implies the automata model of a consumer, which chooses an actions as a function of external parameters, and regression analysis instruments of machine learning
- The relation between the price and user actions is hardly elicited
- As a result, efficiency of demand-side management reduces
- The solution is to account for the rational nature of consumer in machine learning models of appliance use
- Preference learning algorithms provide a relevant tool

UNIVERSAL MODEL OF CONSUMER'S PREFERENCE LEARNING FROM HER ACTIONS

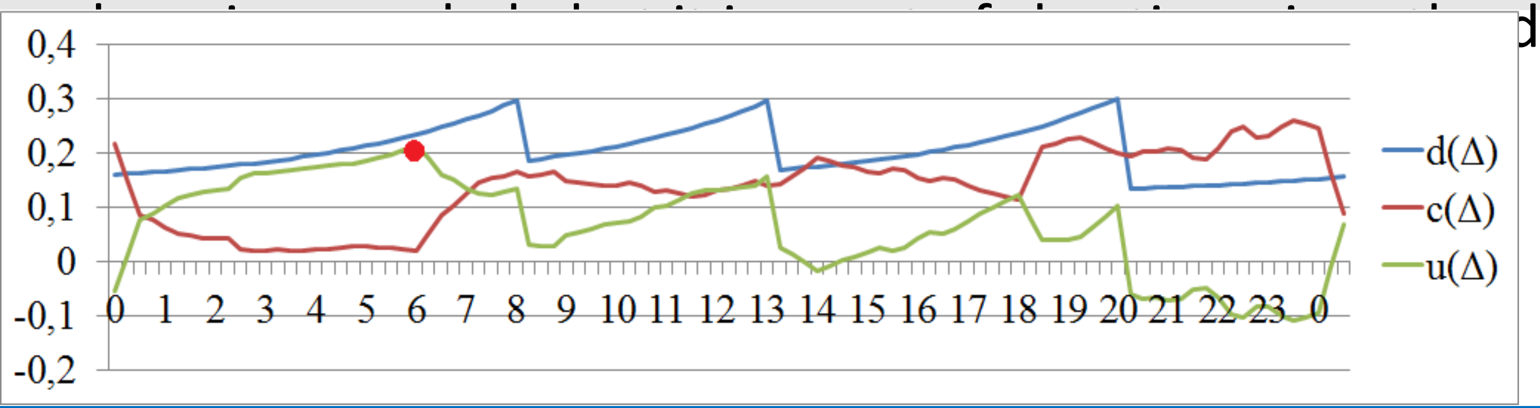


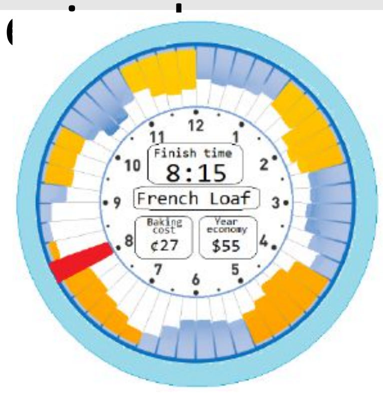


M. Goubko et al. Bayesian Learning of Consumer Preferences for Residential Demand Response. CPHS 2016, Brazil

CONSUMER PREFERENCE LEARNING: THE LESSONS

- Demand response perspective of real-time pricing for residential customers requires changing the paradigm of energy saving automation at home, because manual saving becomes tricky and current algorithms do not generalize to real-time pricing
- Utility-based approach to user preference modeling is the most compact way to catch the “comfort vs. economy” trade-off, which is has to be learned
- Behavioral simulations can provide realistic appliance use scenarios for home automation algorithm analysis and assessment
- It is possible to learn power saving preferences of consumer but it is still the problem to learn them as fast as needed. Collaborative






CLIMATE CONTROL
IN OFFICE BUILDINGS

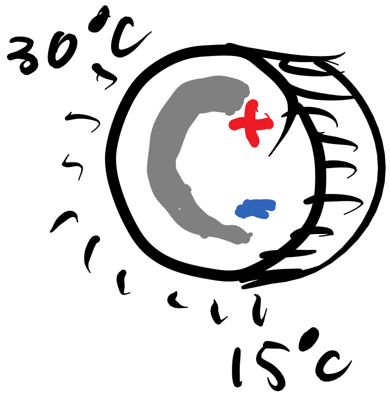
CLIMATE CONTROL FOR COMMON AREAS (WORKSHOPS, CLASSROOMS, OFFICES): PROBLEM SETTING

- Human performance in learning and production depends on the comfort of the environment (in particular, the thermal regime)
- Thermal preferences of different people widely vary
- Offices, shops, and classrooms are typically equipped with a climate control system

- But they still cannot deliver personal environment to every employee/student

CLIMATE CONTROL FOR COMMON AREAS (WORKSHOPS, CLASSROOMS, OFFICES): “CLASSIC” APPROACH

- “Classic” control theory avoids human experience: «We give you a temperature control wheel, and we do not care how you decide which temperature to set».

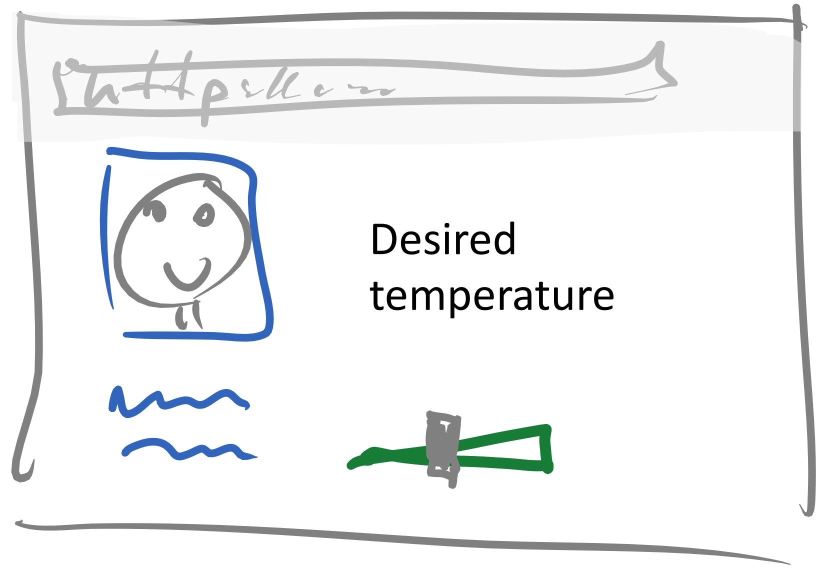


- As a result, «first come – first served» policy results in conflicts.

CLIMATE CONTROL FOR COMMON AREAS (WORKSHOPS, CLASSROOMS, OFFICES): SMART OFFICE APPROACH

- An ICT approach ("smart office", Internet of Things, and similar) suggests automation through informational support
- Office management information system collects employees' requests s_i about the desirable indoor temperature
- The temperature for the common area is chosen from the reasonable compromise

- But how the final temperature to set up is chosen from employees' requests?



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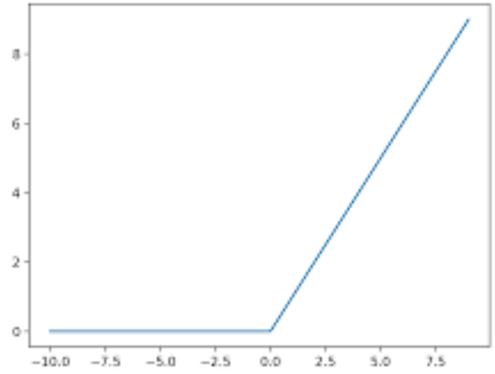
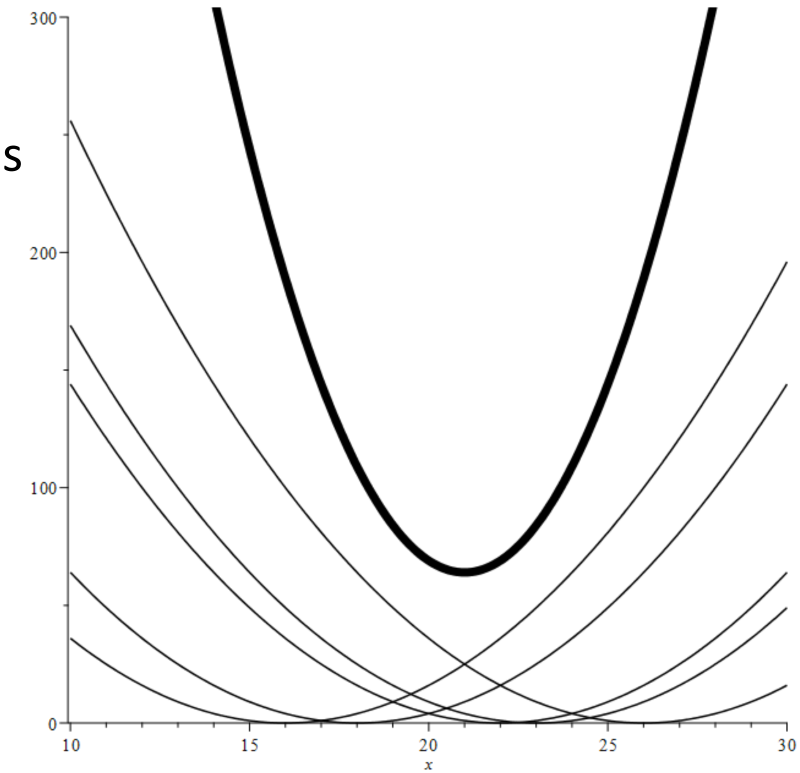


A NAÏVE APPROACH TO USER EXPERIENCE FOR CLIMATE CONTROL IN COMMON AREAS

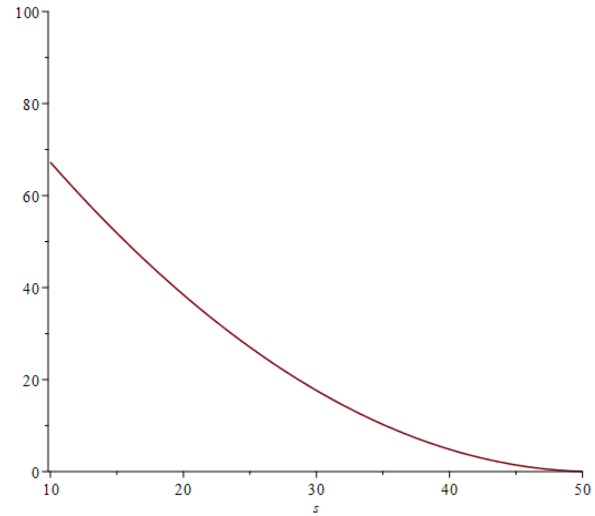
- Every person has her most preferred air temperature r_i , which is assumed constant for some period of time.
- The personal discomfort level from deviations of temperature t from the most preferred temperature r_i is typically modeled with the quadratic function $(t - r_i)^2$.
- Given all preferences equally important, the total discomfort level is written as $\sum_{i=1 \ldots n}(t - r_i)^2$.
- Minimum discomfort level is achieved when $t = \sum_{i=1 \ldots n} r_i/n$, i.e., under average desired temperature.



- After adding an automatic vote elimination procedure for leaving employees (e.g., using access control system), the decision rule (the *mechanism*) goes to production…

A NAÏVE APPROACH TO USER EXPERIENCE FOR CLIMATE CONTROL: THE CONSEQUENCES

- The designers missed an important detail: $s_i \neq r_i$ in general, and the message may not coincide with the true employee's preferences.
- So what we have is a too primitive model of a human, which neglects individual rationality and manipulation opportunities
- What can be a resulting decision when individually rational employees are allowed to vote for the air temperature?

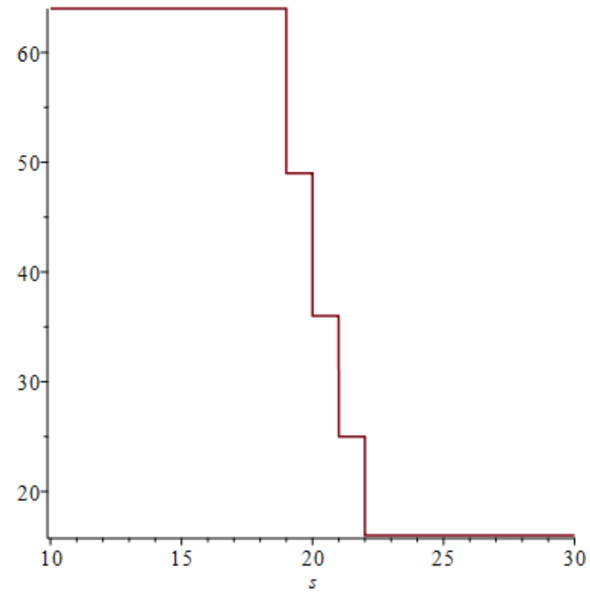


Personal discomfort as the function of message s_i under the average temperature rule for r_i = 27 °C

- Two parties are formed – the members of one party choose the minimal allowed temperature $\underline{t}$, and the members of the other party choose the maximal allowed temperature $\overline{t}$, and the resulting temperature is $(m\underline{t} + (n-m)\overline{t})/n$, where m is the size of the "cold" party.

USER EXPERIENCE FOR CLIMATE CONTROL IN COMMON AREAS USING MEDIAN VOTER SCHEME

- Message manipulation can be avoided by replacing the average temperature rule with the median temperature rule (when the half of votes is above the decided temperature, and a half of votes is below)
- **Med([16,18, 22, 23, 26])= 22**
- An important feature of the median scheme is that **no employee can gain from message manipulation, so it is a strategy-proof mechanism**
- Moreover, the median voter scheme is **the only (!)** strategy-proof mechanism



Personal discomfort as the function of message s_i under the median temperature rule, for r_i = 27 °C

What are the other benefits of the median voter scheme?

MEDIAN VOTER SCHEME: ROBUST MECHANISM

- Strategy-proofness makes the mechanism robust
- Under the average temperature rule the change in the balance of forces (sizes of the "cold" and "warm" parties) may result in the dramatic change of the resulting decision, and to find the new equilibrium all employees have to change their strategies (messages, temperature requests) in a complex an unobvious way.
- Consider an example. Assume two groups of employees share a single open space. The first group has r_1 = 26 ^{o}C and the second one prefers r_2 = 20 ^{o}C. Under the average temperature rule some equilibrium will be set with the maximum allowable request (e.g., 30^{o}C) of Group 1, and the minimum allowable requests (e.g., 16^{o}C) of Group 2. If Grop 1 suddenly leaved, the temperature in the room falls immediately to 16 ^{o}C.
- To stop the temperature decrease and retain the comfort, the rest of employees have to adjust their messages seeking for the new equilibrium (spending the work time).
- No such problems arise under the median temperature scheme.

ENERGY MARKETS AS CONTROL MECHANISMS: EXPERIMENTAL STUDY

MATHEMATICAL MODEL OF ACTIVE CONSUMER

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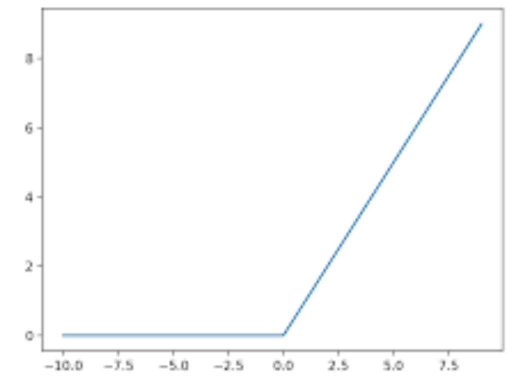
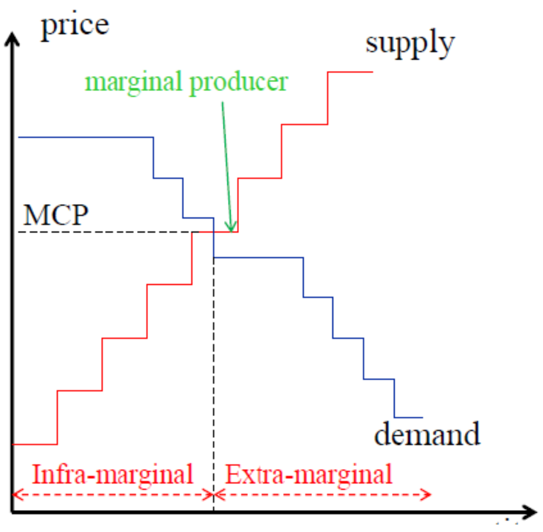


Problems:

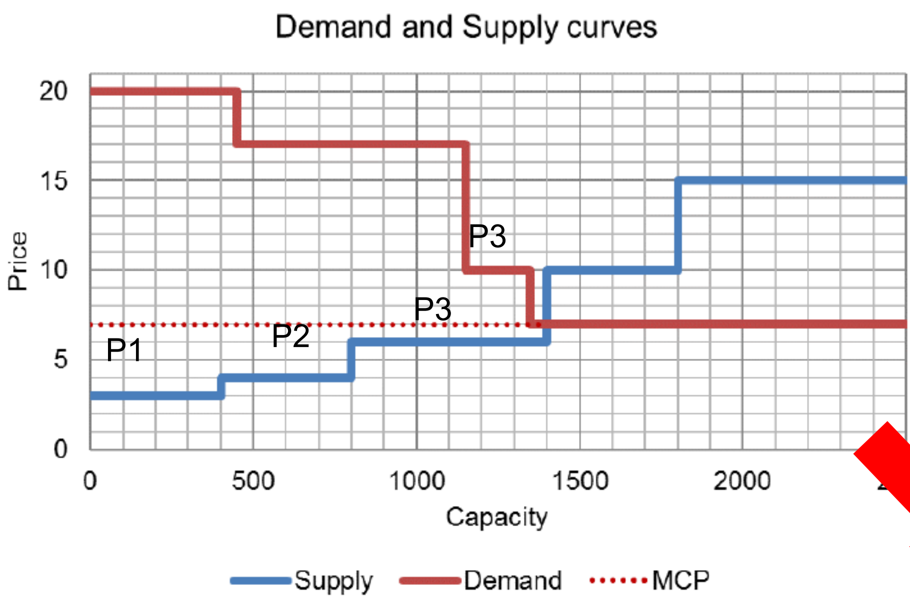
- The electricity market seems to be large, and no participant seems to have market power. But congestion constraints break the whole market into a collection of small nodal markets, where participants have the power to manipulate the prices.
- Vertically integrated corporations in Russia own chains of fuel companies, generating capacities, and distribution. A coordinated strategy gives market power, which is hard to identify

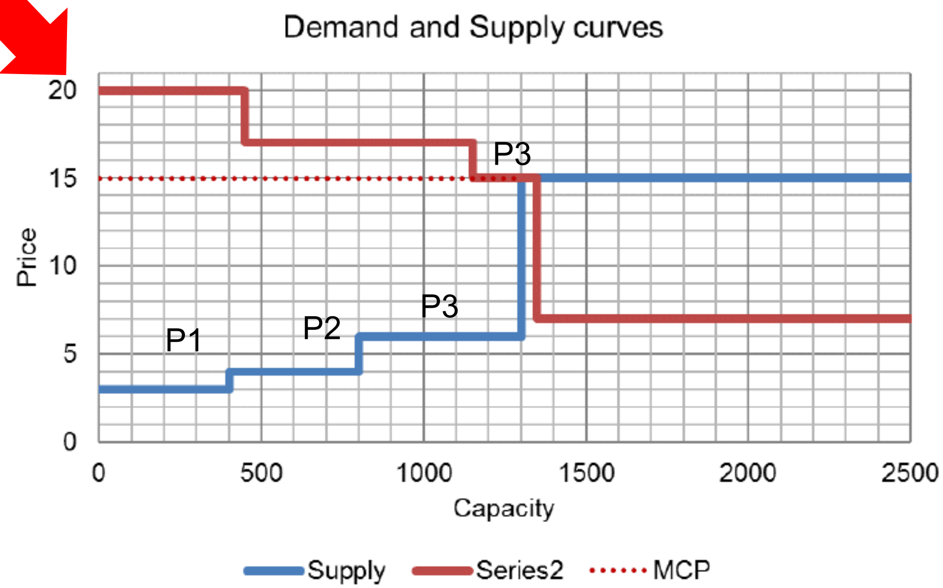


Consequences of market manipulation

- Extra electricity prices
- Grid capacity underestimation
- Unsatisfied demand

MARKET MANIPULATION: GENERATION AND LOAD SHARED

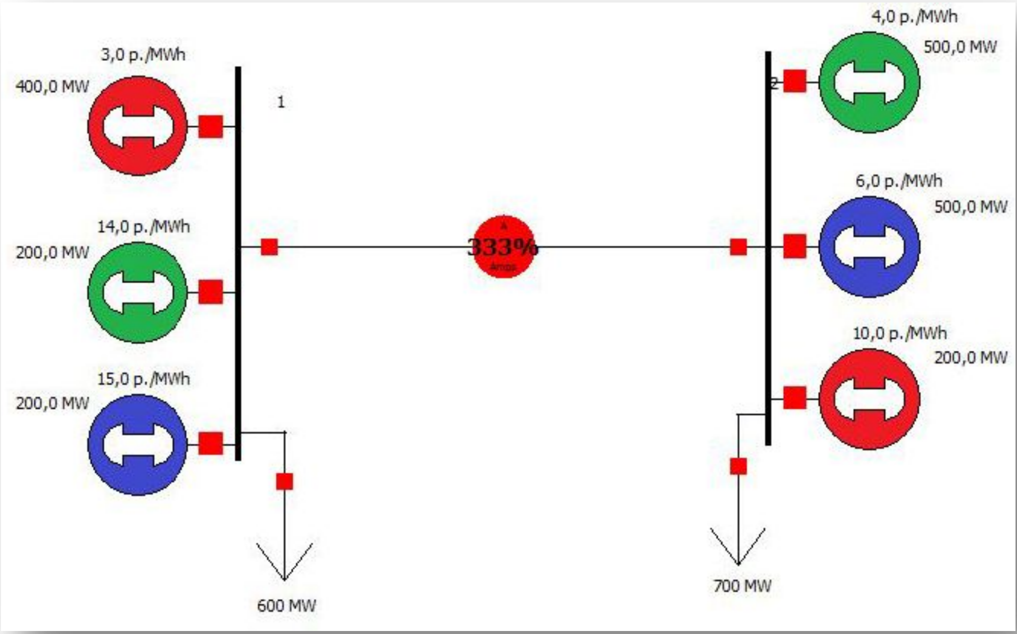




MARKET MANIPULATION: SIMPLE MODEL OF CONGESTION

Model

- 2 nodes connected with a transmission line with possible congestion (max flow limit)
- Three players
- One generator per bus



Market equilibrium (efficient)

Max flow	Price at node1	Price at node2
200	**14**	**6**

Real gaming

Game	Price at node1	Price at node2
1	15	15
2	**18**	**18**
3	17	17
4	10	10

TESTBED OF DIGITAL SOLUTIONS: A SYSTEMATIC APPROACH TO DESIGN AND RESEARCH OF INTELLIGENT CONTROL IN SMART GRIDS

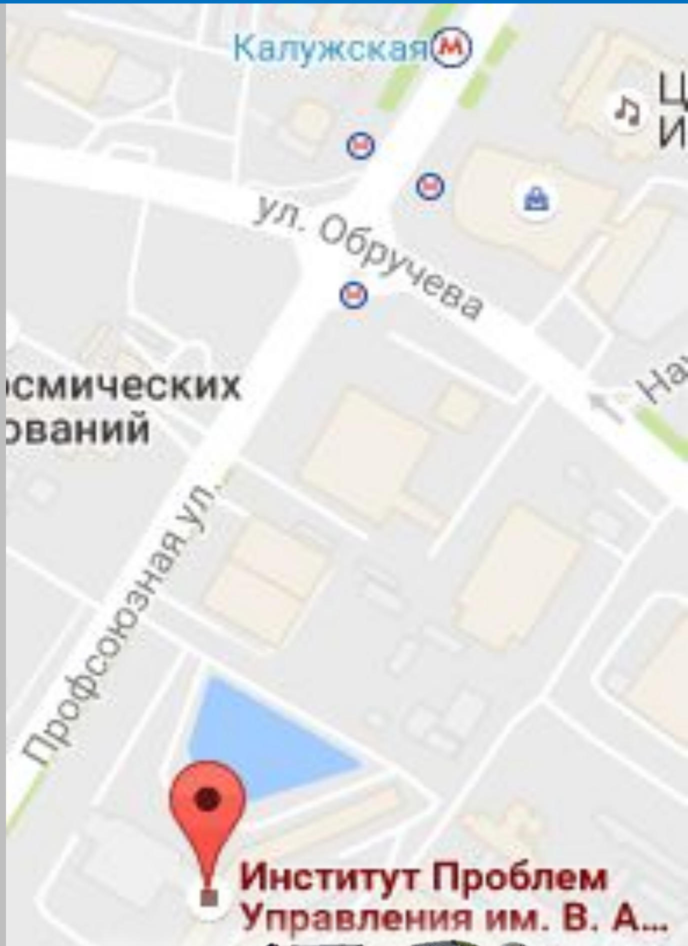
RESEARCH TESTBED OF DIGITAL SMART GRID

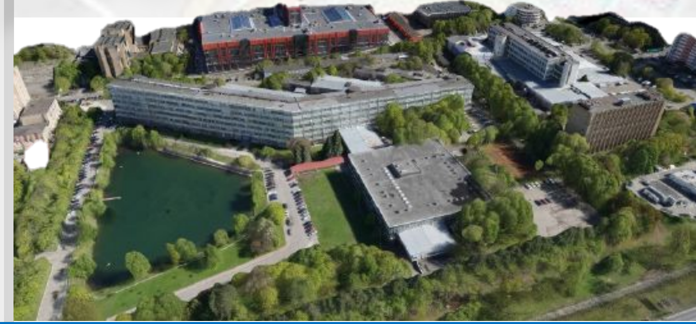
Ideas

- Global digital solutions in a small-scale system
- Less hardware, more algorithms
- Real control object – infrastructure networks or ICS RAS

Aims

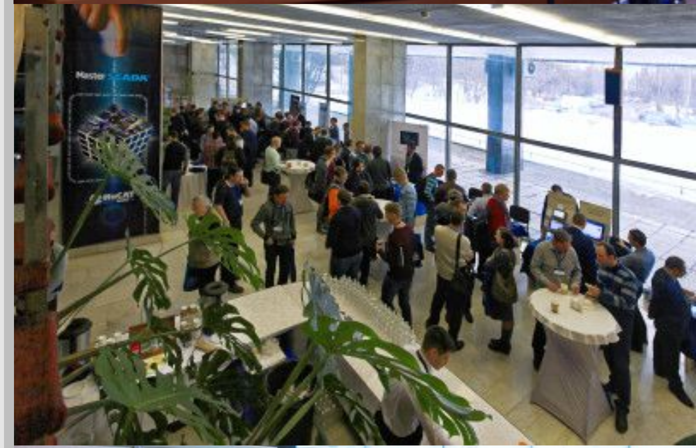
- Research in distribution networks, customers, markets, smart building technologies, etc.
- Data collection for electric loads, heating, microclimate for experiments, model tuning and for the predictive control
- Testing data collection and data mining technologies for distribution network of ICS RAS
- Database of reference datasets for energy research
- Demo and comparative study of technological solutions
- Energy saving for ICS RAS

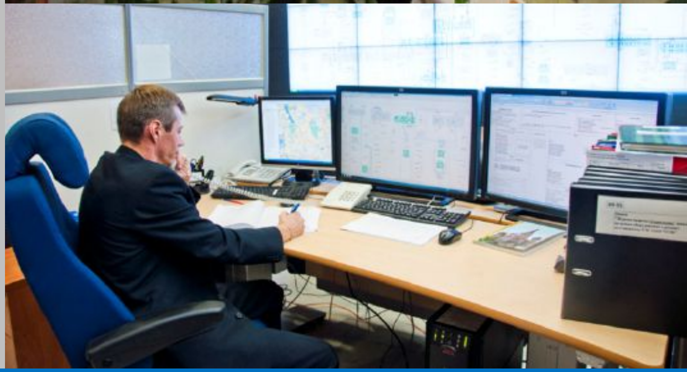




USERS OF THE RESEARCH TESTBED

- **Researchers**
  - ✓ Making field experiments on a real object
  - ✓ High granularity history of loads, heating, climate (>1000 measurements/sec)
  - ✓ Modelling economic relations
- **Innovative technology developers**
  - ✓ Testing technological solutions
  - ✓ Technological solution assessment
  - ✓ Demonstration of new products to clients
- **Field experts**
  - ✓ Reference datasets for solution comparison
  - ✓ Experiments for real analytics
- **Equipment, control instruments, sensors, software vendors, system integrators**
  - ✓ Demonstration testbed for novel technologies
  - ✓ Field study and integral testing of novel solutions
- **Energy staff**
  - ✓ New capabilities of controlling infrastructure networks
  - ✓ Energy saving





INTELLIGENT CONTROL CYCLE IN DISTRIBUTION ENERGY SYSTEM

Data collection (loads, losses, climate)

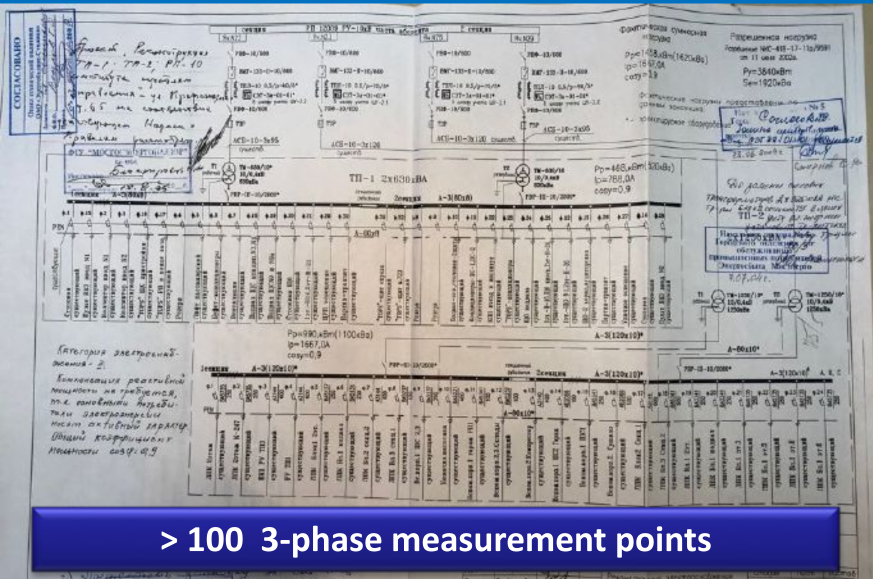
Big data mining and visualization

Agent-based models of consumers

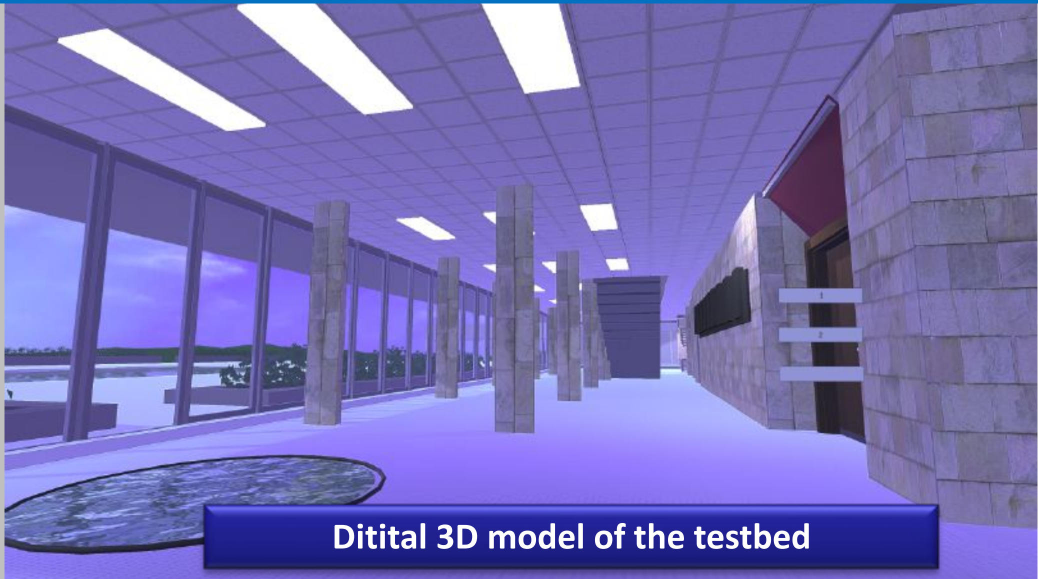
Identification of the system from limited information

AI-based predictive models

ELECTRICAL SUBSYSTEM: METERING AND INFORMARION PROCESSING

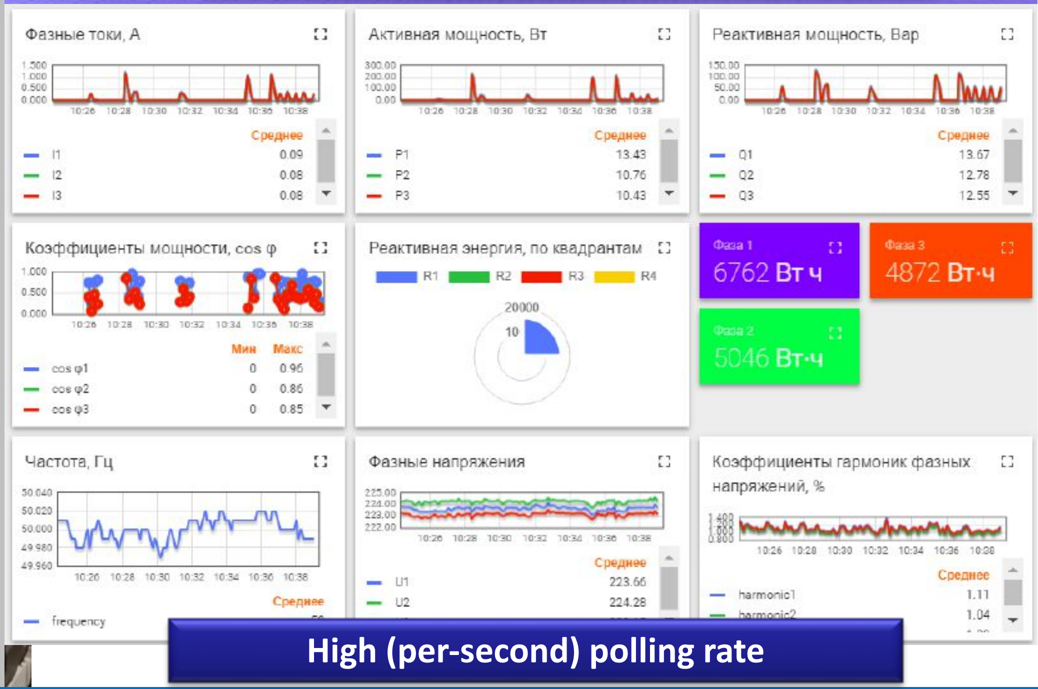


> 100 3-phase measurement points



Ditital 3D model of the testbed

Smart meters: and reactive load measurement



High (per-second) polling rate

HEAT SUBSYSTEM: EQUIPMENT

Contact temperature sensors Vega ТД-11

- Class A device
- Archive of indications
- External temperature sensor
- Internal clock
- The period of contact: 1, 6, 12, 24 hours
- Internal Battery Charge Measurement
- USB port
- The measured temperatures, ° C: -55 ... +100
- LoRaWAN ™ indoor antenna
- The radio range in the city is up to 5 km
- Configurable transmit power (<100 mW)
- 3400 mAh built-in battery capacity
- Battery life up to 10 years
- Case dimensions, mm 95 x 50 x 45

> 50 sensors in the heating system

Heat and flow meters

- 4 pulse inputs
- Pulse frequency <200 Hz
- 2 open collector outputs
- Up to 4 security entrances
- USB port
- Range of working temperatures, ° C - 40 ... + 85
- Built-in temperature sensor yes
- Class A or C depending on external power
- 16 LoRaWAN ™ channels
- The communication period is 1, 6, 12 or 24 hours
- LoRaWAN ™ indoor antenna
- External power 5 V
- Case dimensions, mm 95 x 50 x 45

> 2 measurement points

MICROCLIMATE SUBSYSTEM: EQUIPMENT

1. **Room microclimate wireless sensors**


2. **Outdoor wireless climate sensors**


3. **Automatic weather station (wind direction, pressure, humidity, rain, …)**

ELSYS ERS, ERS Eye, ERS CO2

- Temperature
- Humidity
- CO2 (variant)
- Light
- Motion (PIR)
- Volumetric (variant)

ELSYS ESM 5k

- Temperature
- Humidity
- Light
- Acceleration
- PIR motion sensor (optional)

The Weather Station LoRaWAN

- Temperature
- Humidity
- Rain
- Wind Speed
- Wind Direction
- Dew Point
- Wet Leaf

ELSYS ESM 5k

- Temperature
- Humidity
- Light
- Acceleration
- PIR motion sensor (optional)

Digital technologies for data collection and processing

1. Extremal performance modes of wireless sensor networks
2. Information security of digital distribution networks
3. Complex analysis of cybersecurity in infrastructure networks

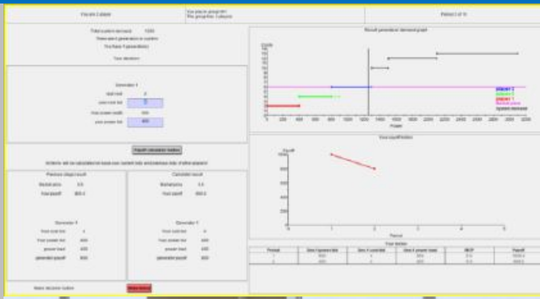
Intellectual analysis of infrastructure networks

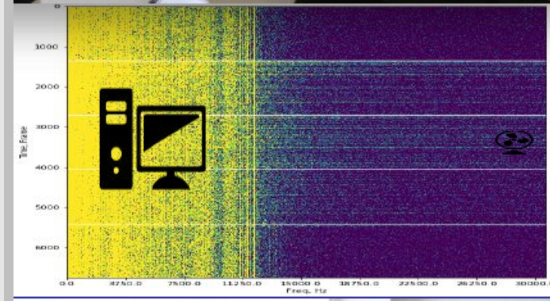
1. Network structure learning from signals
2. Technologies for losses localization and minimization in networks
3. Practical energy disaggregation (non-intrusive load analysis)

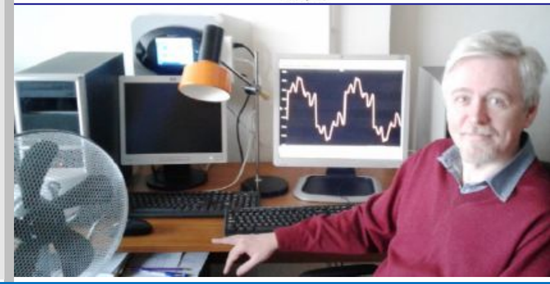
Theoretical foundations of digital services for network company

1. Robotized energy system control center
2. Predictive diagnostics of electromechanical systems
3. Stability control in distributed generation networks
4. Network topology optimization and expansion planning

Theoretical foundations of digital services for active consumer







LOAD FORECASTING WITH REGRESSION AND AGENT MODELS

Motivation:

- Load forecast is an essential element of energy management system of a single customer or a group of customers (up to the region)
- Sometimes, the behavior of active consumers can be predicted from regression models (ARIMA and alike). However, often we need to consider a consumer as a rational agent, and to derive her behavior from her preferences (goal function).
- Sensitivity of a consumer to price signals is a key feature required in demand response calculations
- Existing load prediction models neither account for new technological capabilities (distributed generation, batteries) of consumer nor account for the effect of "consumer in a control loop"
- Efficient load prediction algorithms are highly demanded by market

Andrei Makarenko
Head of Department, PhD

- **Data analysis**
- **Machine learning**

Andrei Rogatkin
MIPT alumni
Research fellow, math and electonics

Ruslan Portsev
researcher
AI, computer vision, deep learning

Project Objectives: Develop algorithms to predict household, utility and commercial consumers' loads taking into account their capabilities for distributed generation and load shift, their use of energy management systems.

Approach: deep learning, simulation multi-agent models based on consumer behavioral models

Perspective: a universal multi-agent modeling environment for electric power markets, development of market brokers for microgrid markets

PRACTICAL ENERGY DISAGGREGATION (NON-INTRUSIVE LOAD ANALYSIS)

Andrei Makarenko
Head of Department, PhD

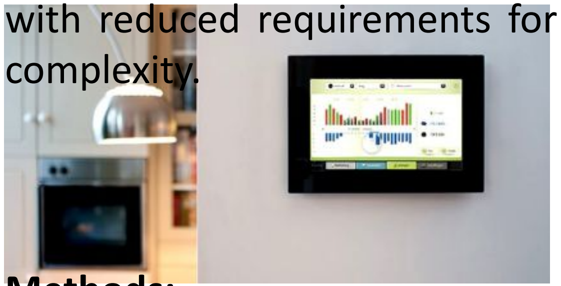
- **Data analysis**
- **Machine learning**

Andrei Efremov
researcher
Information systems

Motivation:

- **Energy disaggregation** decomposes the load of a group of appliances measured by one smart meter into the contributions of individual appliances
- It can reduce the metering cost, energy audit and energy saving projects
- Intellectual analysis of active and reactive load, current and voltage spectra
- Existing methods are highly demanding to the signal quality, measure frequency, or leaning set volume and granularity

Project objectives: develop effective energy disaggregation algorithms with reduced requirements for the quality of source data and their complexity.



Approach: A promising approach is to use deep artificial neural networks (deep learning), when labor-intensive neural network learning algorithms are applied only to the unrecognized balance of consumption of each meter and are executed in the cloud service, while computationally undemanding recognition algorithms work at the level of individual meters. The storage of signatures of constantly running appliances helps to disaggregate their consumption.

Methods:

a) smart metering technologies for collecting, storing and transmitting information about the power consumption of a group of devices

b) data mining, including deep artificial neural networks (deep learning)

Perspectives: The developed methods can be used to identify network events that are not related to changes in the operation modes of individual electrical appliances, but are important for dispatch control of the distribution network: for detecting and localizing accidents, changing the network topology as a result of relay operation. A key feature of the approach is the use of limited measurements at the minimum cost of additional electrical equipment and a communication system).

ARCHITECTURE AND MECHANISMS OF ENERGY MARKETS IN MICROGRIDS

Motivation:

Before new market policy is implemented it must be tested

An important aspect is the analysis of the manipulability of control mechanisms - the ability of market participants to benefit from the message of false information.

The analysis of manipulability and the search for optimal mechanisms requires the use of game theory methods and mechanism design

Currently, there is no systematic analysis of manipulability in the development of promising policies for the electricity markets.

Nikolai Korgin

Dr.Sci., laboratory head

Mechanism design, gaming, management science

Vsevolod Korepanov

PhD, chief researcher

game theory, information systems

Project Objectives:

1. Improving the wholesale electricity market (W

• Game-theoretic model of the wholesale electri t

• Recommendations for strategy-proof rules of e market based

• Methodology for detecting local markets on the wholesale market

2. Improving mechanisms for cross-border electricity trade

• Game-theoretic models of foreign wholesale electricity markets (Nord Pool, Baltic)

• Recommendations on trading based on a game-theoretic analysis of the market

• Recommendations for improving the rules of international electricity markets and unions

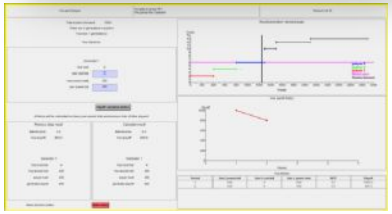
3. Microgrid market research

• Game-theoretic models of promising retail markets with distributed generation

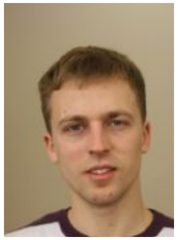
• Recommendations on the architecture of the retail microgrid market, taking into account the manipulability

Approach:

Game-theoretic analysis of basic scenarios, business games with experts to



АНАЛИЗ ПРЕДПОЧТЕНИЙ ПОТРЕБИТЕЛЕЙ И ЭНЕРГОСБЕРЕЖЕНИЕ



Nikolai Bazenkov

PhD, chief researcher

ad-hoc networks , AI

Motivation:

An impressive application of artificial intelligence and machine learning methods has become the technology of "smart" environments ("smart" home, office, city), allowing automatic or interactive control of the functions of the living environment. World technology leaders are already bringing home automation systems (Amazon Alexa, Google Home, Samsung Smartthings, Facebook Jarvis, Hitachi HEMS, Honeywell Z-Wave) to the market, which in the United States alone, according to McKinsey, exceeded $ 29 billion in 2017. An important advantage , obtained by buyers of such systems, are advanced features of energy saving. However, existing approaches limit demand management, as price signals are not perceived by consumers using home automation systems.

Project objectives: Development of control algorithms for household appliances for the balance of comfort and energy saving based on identifying the user utility function by the history of interaction with him.

Approach: Identification of user preferences and taking into account the rationality of their behavior to achieve the best balance of comfort and cost of electricity in the process of managing home electrical appliances. The problem of the lack of real data for testing and selection of different approaches is solved using behavioral models of rational control of electrical appliances based on the utility function. The novelty of the approach is the combination of an active consumer model, which includes solutions for the use and generation of electricity, machine learning algorithms to identify individual consumer preferences, and their implementation in an open, scalable software platform.

Research Methods:

a) Multi-agent modeling of rational behavior for the analysis of training problems and the generation of source data. The optimal control problem that arises in modeling is solved by the methods of dynamic programming and adaptive dynamic programming (reinforcement learning).

b) Preference learning methods: inverse reinforcement learning, Bayesian learning, approximate Bayesian computation.

Object of study: the environment of the "smart" home, partially or fully automated household electrical appliances

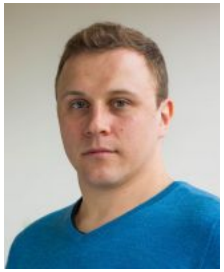
Potential customer: manufacturers of household appliances and home automation systems

Prospects: The developed algorithms for identifying the user utility function should find application in the technologies of automatic and automated (in the mode of an adviser system) control of household electrical appliances.

МОДЕЛИ ТЕПЛООБМЕНА И УПРАВЛЕНИЕ МИКРОКЛИМАТОМ

Motivation:

Currently, manual climate control is widely used in residential, office and public spaces (opening / closing the window, on / off heater), largely due to the low prevalence of control devices. Public premises place high demands on air quality (for example, hospitals, kindergartens), energy efficiency (hypermarkets, shopping centers) and are equipped with the necessary sensors and devices, but all devices are independently controlled. Smart climate devices are gradually entering the mass market and gaining popularity among the population. Moreover, progressive construction companies declare energy efficiency and enhanced climate management capabilities in their buildings. The construction of an integrated climate control system is complicated by the lack of an adequate model and / or lack of data from existing sensors and methods for their processing. Existing building models are based on solving non-linear equations of heat-mass transfer (Navier-Stokes). When analyzing macrocharacteristics of air (average temperature, humidity, CO2 concentration) in complex multi-zone rooms, simplified models are needed that describe the change in air characteristics on a minute scale.



Yuri Rassadin

researcher

sliding-mode control , mathematical modelling

Project Objectives:

1. Construction of an improved model of the dynamics of indoor air characteristics.
2. Development of identification algorithms for the constructed model based on incomplete measurements.
3. Development of algorithms for optimal control of microclimate forming devices, search for optimal operating modes taking into account the balance of group comfort and energy conservation.
4. Analysis of various operating modes, taking into account the possibilities of distributed generation and consumption shift.
5. Implementation of the developed control algorithms on the basis of the Polygon of control in the electric power industry of IPU RAS.

Approaches and research methods: Optimal control, predictive model control methods (MPC), machine learning methods, distributed optimization

Prospects: The developed climate control algorithms can be used in lower-level models in the task of forecasting the energy consumption of office buildings.

ИДЕНТИФИКАЦИЯ СТРУКТУРЫ СЕТЕЙ ПО СИГНАЛАМ В УЗЛАХ

Motivation: The existing energy audit procedures in practice are substantially complicated by the absence or inaccuracy of information about the structure and current state of the Customer's engineering networks. It is possible to automate the costly and lengthy procedure of manually building the actual scheme of engineering networks, as well as identifying the state of its nodes and connections, using modern methods of measurement and intelligent signal processing based on information from sensors located in network nodes. Ideally, after a relatively short collection of dynamic signals from sensors installed at key points of the electric, thermal, ventilation network, the network topology should be fully restored and the current state of devices and communication lines should be identified (whether it is active or wave resistance in the electric network, effective cross-section of pipes or heat loss in the heating network, etc.). In practice, the implementation of this idea requires solving both fundamental mathematical problems (creating disturbance propagation models in networks of various nature, developing effective topology identification algorithms) and complex technical problems (creating energy-efficient high-frequency sensors, developing economical information transmission and processing schemes ...).

Sergei Parsegov

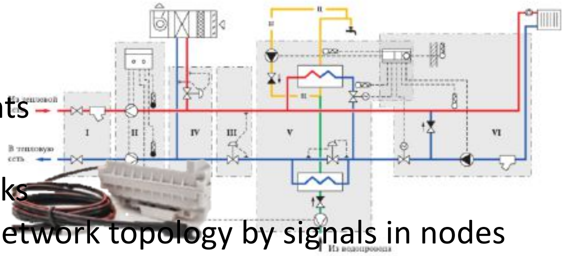
PhD, researcher

optimization, multi-agent systems

Sergei Dushin

PhD, researcher

electronics, wireless networks, signal processing



Project Objectives:

1. Creation of own firmware of autonomous temperature sensors (LoraWAN) with elements of EDGE calculations and incremental quantization of a signal
2. The choice of the causality model of the propagation of disturbances in heating networks
3. Development and performance analysis of optimization algorithms for identifying the network topology by signals in nodes
4. Development of a methodology for an active experiment in identifying the structure of a heat network and collecting data for tuning models
5. Testing the developed models and algorithms on real data of heat networks of the Institute of Public Relations of the Russian Academy of Sciences and municipal consumers of Moscow
6. Development of methods for parametric identification of the technical condition of the heating network and their testing on real data

Approaches and research methods: discrete optimization, machine learning, intelligent signal processing

Prospects: The developed methodology for restoring the topology and identifying the state of utility networks will significantly reduce the time and financial costs of analyzing utility networks, energy audits, etc. of events

ПОВЫШЕНИЕ ПРОПУСКНОЙ СПОСОБНОСТИ СЕТЕЙ АВТОНОМНЫХ УСТРОЙСТВ, ПОСТРОЕННЫХ НА ОСНОВЕ ТЕХНОЛОГИЙ LPWAN

Sergei Dushin

PhD, researcher

electronics, wireless networks, signal processing

Sergei Frolov

PhD, researcher

electronics, wireless networks, signal processing

Motivation: The introduction of the concept of the Boarding of Things is impossible without the organization of reliable communication channels between the measuring and (or) control peripherals (sensors, controls) and application servers.

Among the variety of types of connected peripheral devices, wireless stand-alone devices stand out in a special class, the distinctive features of which are battery power and connection to a higher infrastructure through energy-efficient long-range networks (LPWAN).

Typical disadvantages of this type of device are their limited battery life and low bandwidth of the communication channel to the server. Today, these shortcomings are a significant obstacle to the deployment of large-scale networks, implying a large number of such devices, as well as intensive data collection, often necessary to identify the behavior of the observed systems.

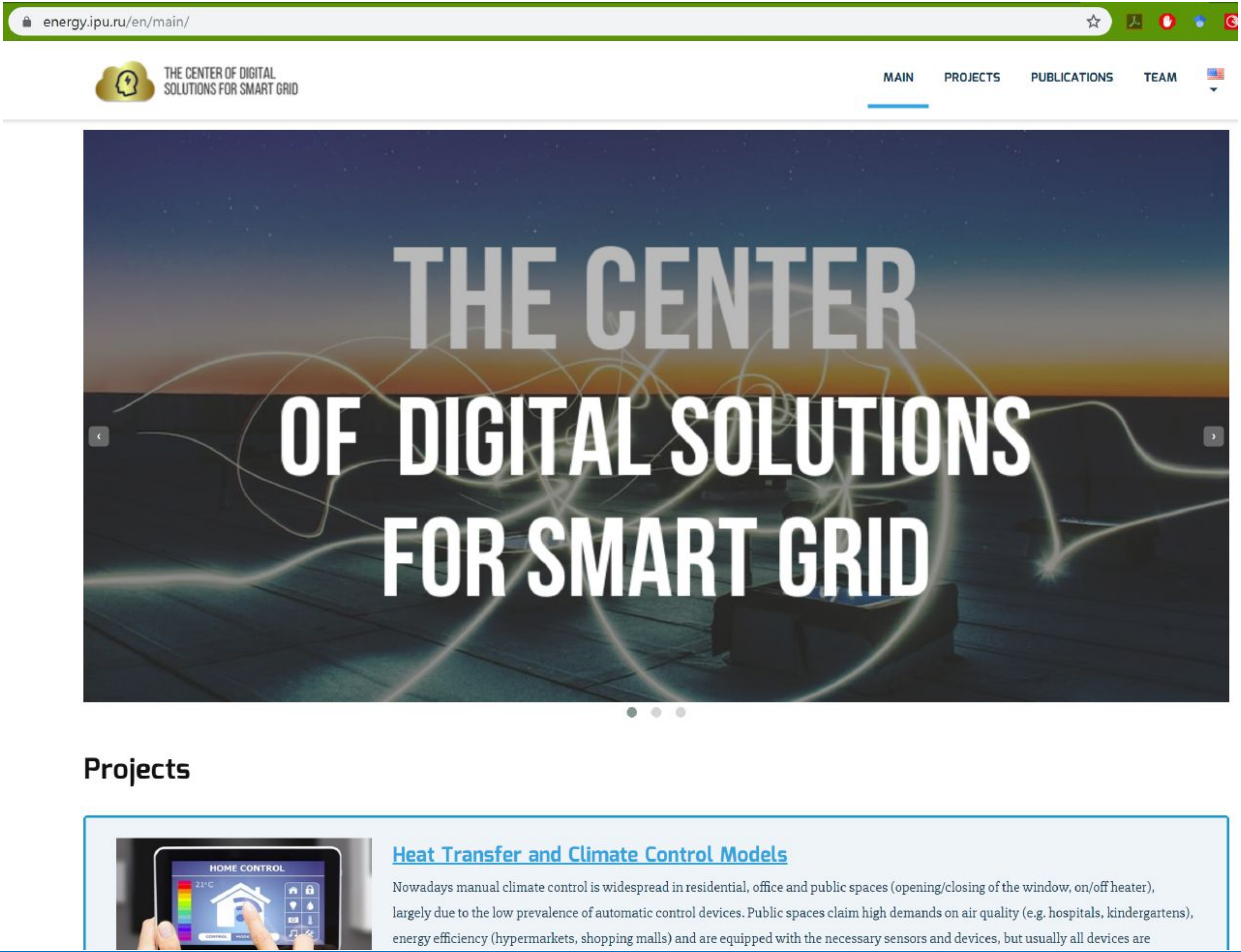
The specifics of stand-alone LPWAN devices require non-standard approaches to the task of increasing the throughput of communication channels. In particular, battery powered peripherals exclude the use of computationally complex algorithms for compressing useful information on their side. In addition, for many applications, a significant data delay is not allowed, the introduction of which is inevitable when applying classical approaches to the problem of information compression. In this regard, solving the problem requires alternative approaches, in particular, based on the concept of distributed computing.

Project objectives: Development of distributed algorithms for compressing information transmitted from peripheral devices to the server, with a high compression ratio and low computational complexity on their side, as well as without significant data delays.

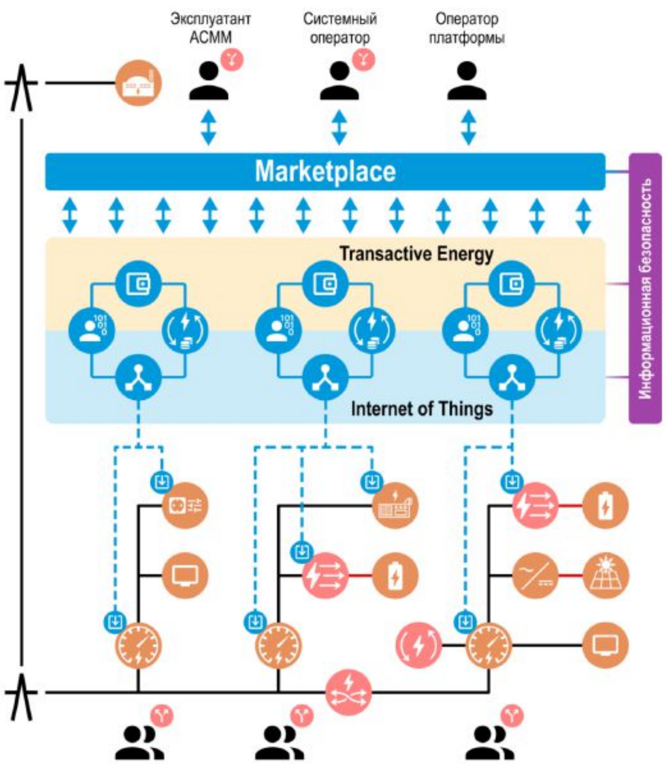
Approach: digital signal processing, linear signal prediction, intelligent processing, distributed computing, peripheral computing.

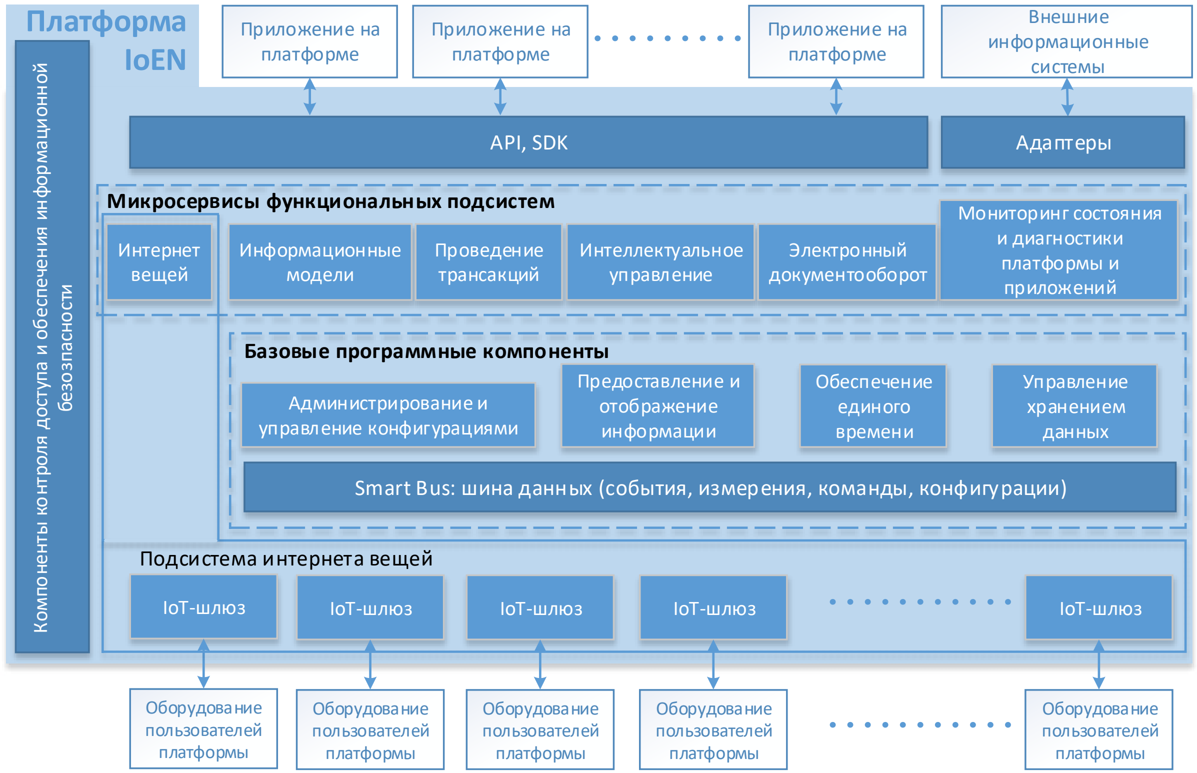
Perspectives: Algorithms for effective compression of information transmitted by wireless stand-alone devices will increase the total number of sensors and control devices connected to the network, as well as provide intensive data exchange in applications requiring active exchange and control in real time.

IPUENERGY.NET: ICS RAS CENTER OF DIGITAL SOLUTIONS FOR SMART GRID



A-PLATFORM: AN INTEGRATION PLATFORM FOR INTERNET OF ENERGY (IoEN)





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ФЕДЕРАЛЬНОЕ ГОСУДАРСТВЕННОЕ БЮДЖЕТНОЕ УЧРЕЖДЕНИЕ НАУКИ
ИНСТИТУТ ПРОБЛЕМ УПРАВЛЕНИЯ
ИМ. В.А. ТРАПЕЗНИКОВА РОССИЙСКОЙ АКАДЕМИИ НАУК