



Project RESPONSE on Improved Modelling of Electric Loads for Enabling Demand Response by Applying Physical and Data-Driven Models

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Riga.

The consortium of the project RESPONSE

- Funded by the Academy of Finland, New Energy Programme
- 2015 – 2018
- **Consortium PI:**
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- **PIs of sub-projects and sites of research**
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- **Key researchers**
 - M.Sc. Antti Mutanen (TUT), Prof. Hannu Koivisto (TUT)
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 - Dr. Harri Niska (UEF)

New needs and opportunities in load modelling

- **The traditional load modelling** either **does not include any control response models** or the response models are static or nearly static. For example, they do not take into account the fact that the responses and their dynamics depend very much on the variations of the ambient temperature and time of occurrence (i.e. time of the day, weekday/weekend, season of the year).
- In future smart grids, the modelling needs are very diverse and **response models are needed both for aggregated responses of customer groups and for individual customers**. Electricity markets and system level power control benefit from customer group models, whereas individual customer models are needed by low voltage network control and customer energy management.
- **New data is now available**. In Finland, smart hourly interval metering has been now rolled to almost all customers. Together with other opening data it enables further development and update of new data-driven models and schemes for load and response forecasting.
- The **analysis** of the influence of weather forecasting errors, performance criteria and confidence intervals on load and response forecasting **was often** omitted or **inadequate** and should be evaluated more extensively.



Main objective in the project Response

- Objective 1
 - **Develop enhanced models for electric load forecasting required by load control operations and distribution network operation**
- Supporting research hypotheses / approach
 - Hybrid models can combine the benefits of the different load modelling approaches, thus providing models that
 - (a) forecast relatively accurately in different situations including also those that have not been experienced before,
 - (b) adapt to changes in the load behavior, especially to those that can be expected
 - (c) are reasonably easy and fast to maintain and update.
 - Models that combine all relevant available information can forecast more accurate than black box models that are based purely on measurement data or models that are purely physically based.

Objectives in the project Response

Building, weather and socioeconomic data (derived from opening public registers)

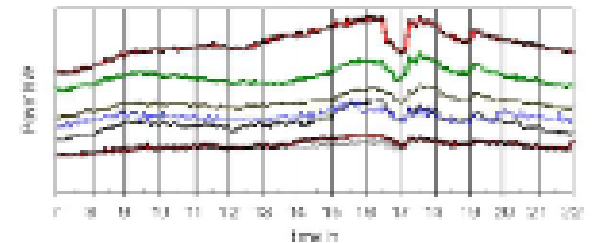
Measurements from smart meters and/or substations, and field tests

Enhanced utilisation of smart metering data and other datasets (Objective 3)

Development of improved load and response forecast models based on data-driven and physical modeling methodologies (Objective 1)

- can forecast accurately in different situations
- enhanced capability to adapt to changes in load behavior
- are easy to maintain and update

Forecasted load and responses in different meteorological conditions, physical and socioeconomic environments and control scenarios



Evaluation and criteria for the performance of load forecasting (Objective 2)

Hybrid approach for combining the strengths of different methods

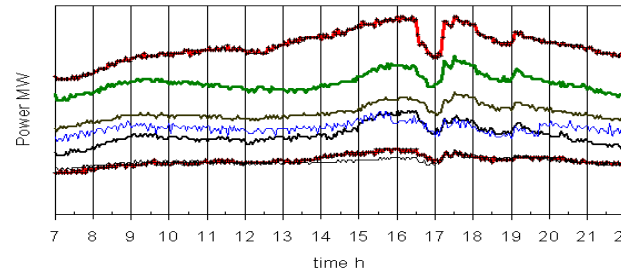
- Machine learning methods are widely and successfully applied.
- They tend to fail, when the inputs are outside those adequately included in the training data.
- Thus the nonlinearities and saturation of the heating and cooling make black-box machine learning based forecasting inaccurate, especially in extreme and rare weather situations and when dynamic load control signals are applied.
- Solution studied: Forecast the dynamics, saturation and control responses of the thermal processes using physically based model structures. Forecast the residual, its time dependencies (seasonal, weekly, daily etc.) and its thermal dynamics using black box machine learning.

Physically based models of load responses

for short term forecasting and optimisation to control actions and temperature variations were based on measurements from power distribution primary substations, smart meters, weather data, and generic building properties. They model aggregated behaviour of groups of mutually roughly similar houses.

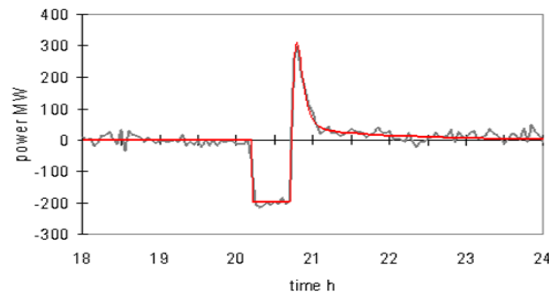
requirements on buildings
building type
other information on building properties

measurements from smart meters and/or substations

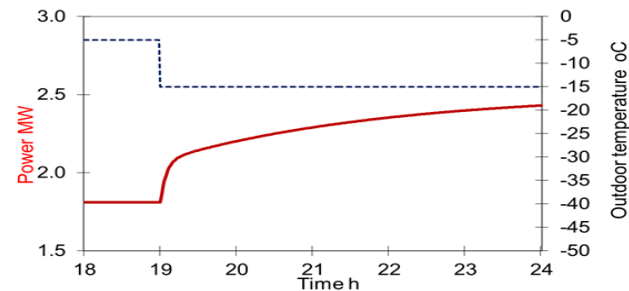


simple physically based dynamic models

modelled response to load control (e.g. pulse response)

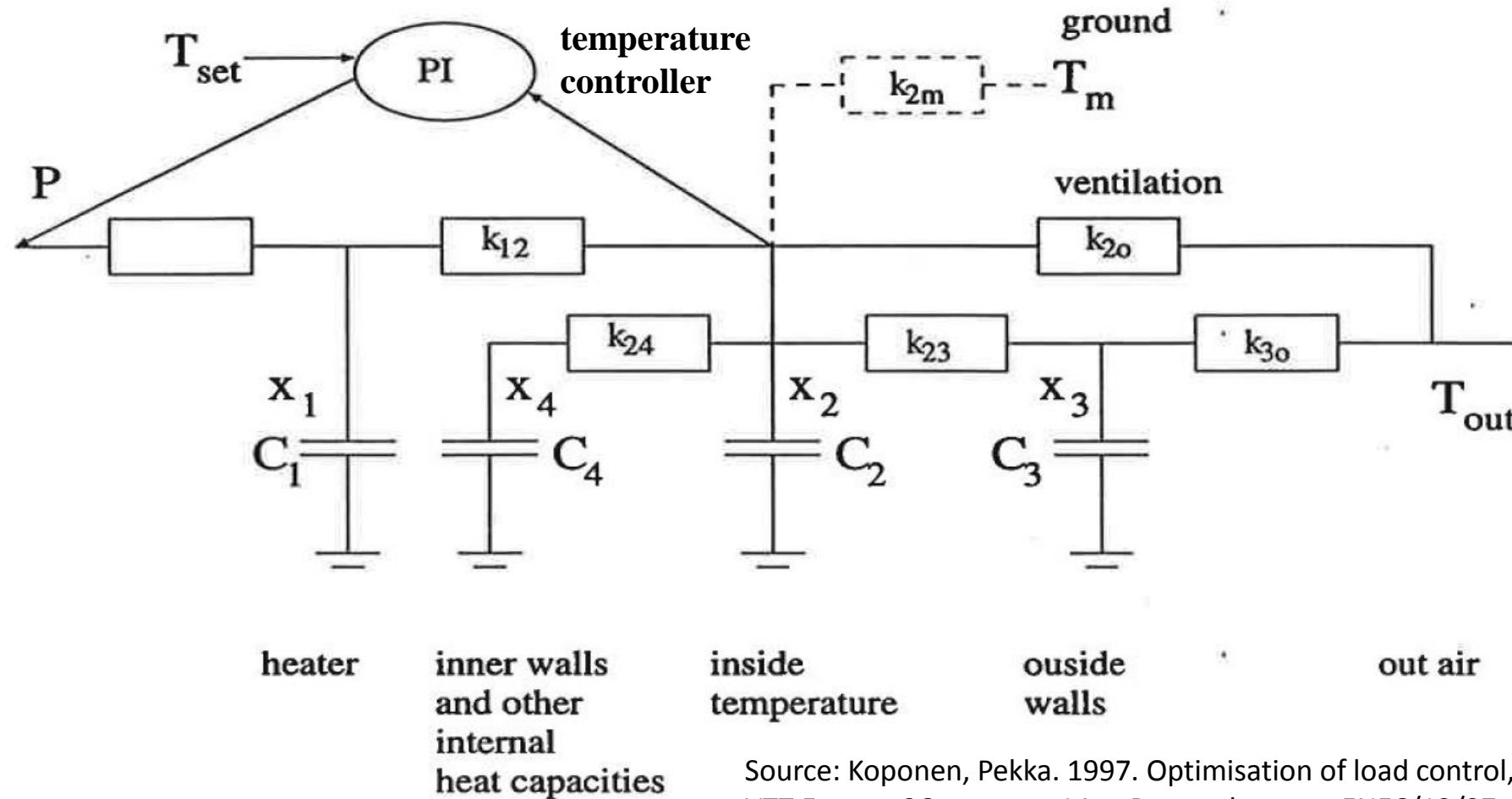


modelled response to outdoor temperature (e.g. step response)



- Hourly interval from smart meters
- 3 minute interval from substations

Structure of the model for the emergency load control responses in the partial storage heating case



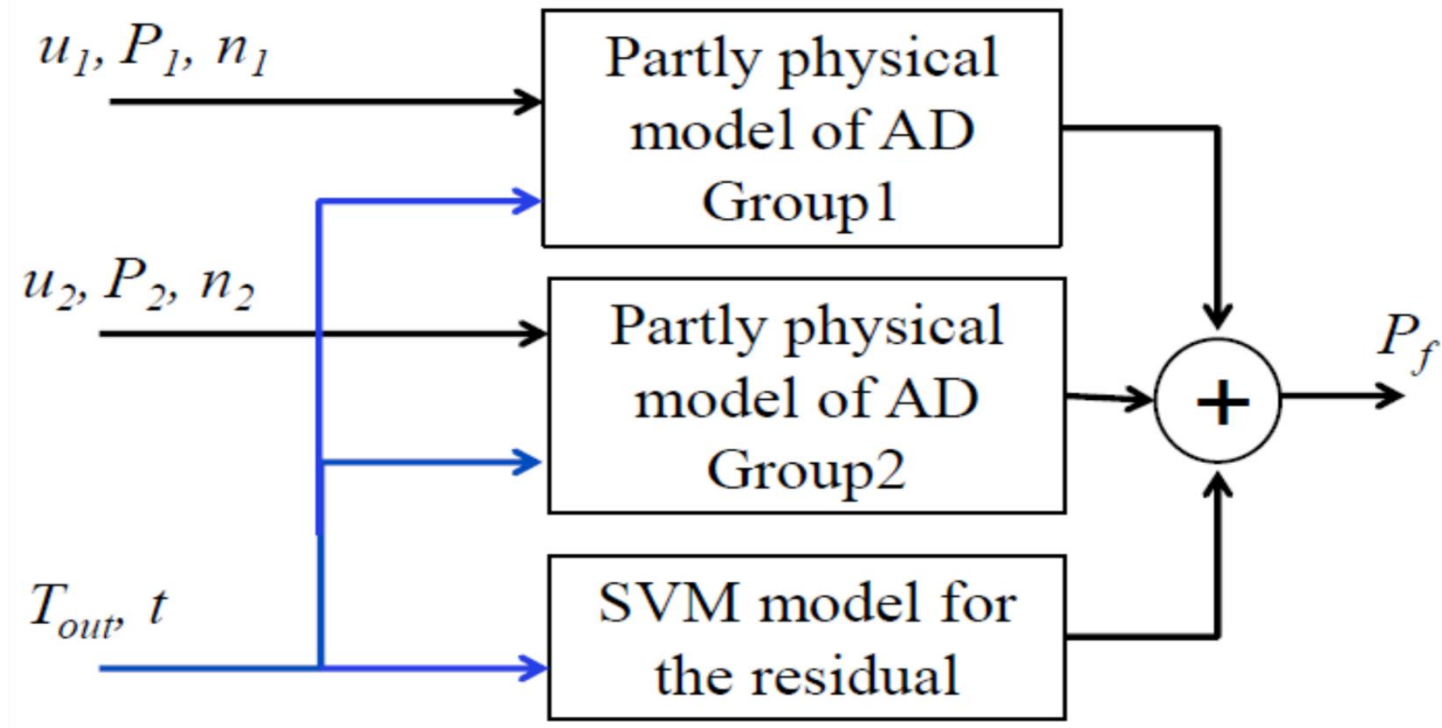
Source: Koponen, Pekka. 1997. Optimisation of load control, Final report, VTT Energy. 26 p. + app. 14 p. Research report ENE6/12/97

The machine learning methods

- Two machine learning based time series forecasting methods have been applied so far
 - Multi Layer Perceptron (MLP) artificial neural network
 - Support Vector Regression (SVR) also called as Support Vector Machine (SVM)
- The machine learning methods are made to model also the system time dynamics. This makes the manual definition of their structure infeasible.
- Genetic algorithm was applied for the optimization of the structure of the machine learning methods.

The main hybridization method is based on adding new methods to forecast the residual of the primarily applied methods.

(in some cases also another hybridization method was applied to support)





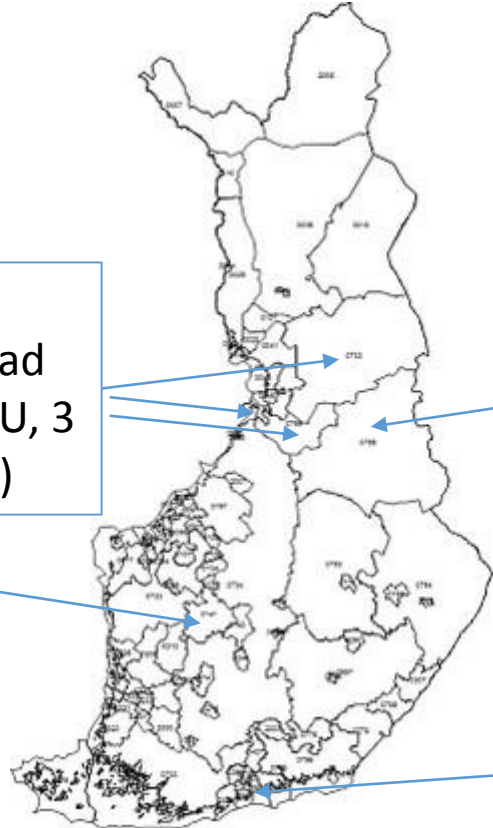
The developed methods have been tested using field test data from various Finnish distribution areas

2009 - 2010
(ToU, KSS)

1996-1997
(emergency load control and ToU, 3 power utilities)

2011-14
(emergency load control and ToU, Loiste)

2012-2014 (spot price based dynamic direct control of full storage heating, Helsinki)

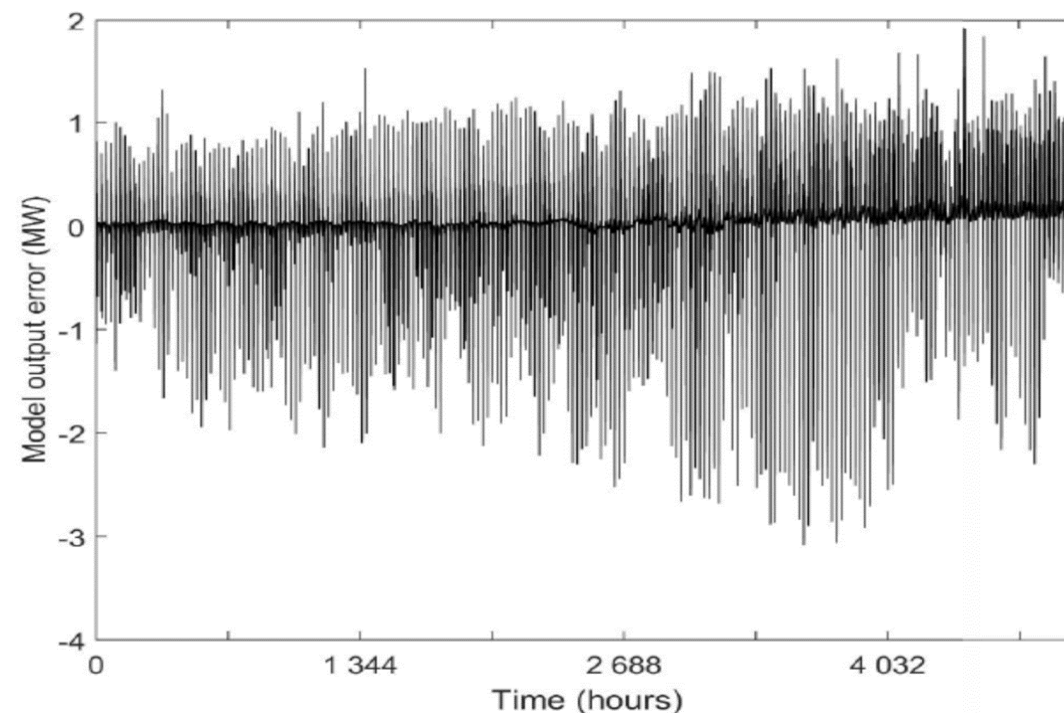
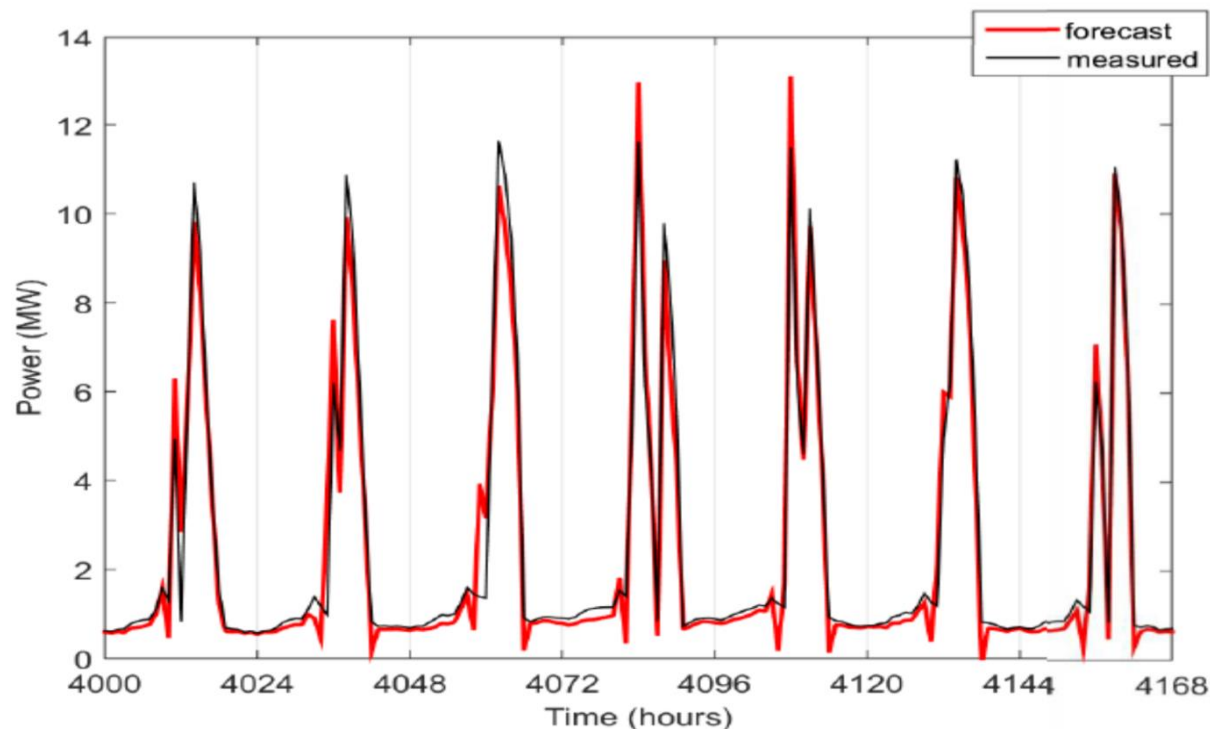


Weather data for this research originate both from the Finnish Meteorological Institute and from the energy companies.

Source of the map is Adato Energia Oy

Case 1: Spot price based control of full storage heating with electricity. Forecast and measured power during a week verification in the full storage case. Forecasting error during the whole verification period

Helen



Every night the heating is turned on so that the forecast heat demand is met with minimum electricity cost. Thus the heating hours are not fixed but change dynamically. This forecast was made 9 a.m. the previous day.



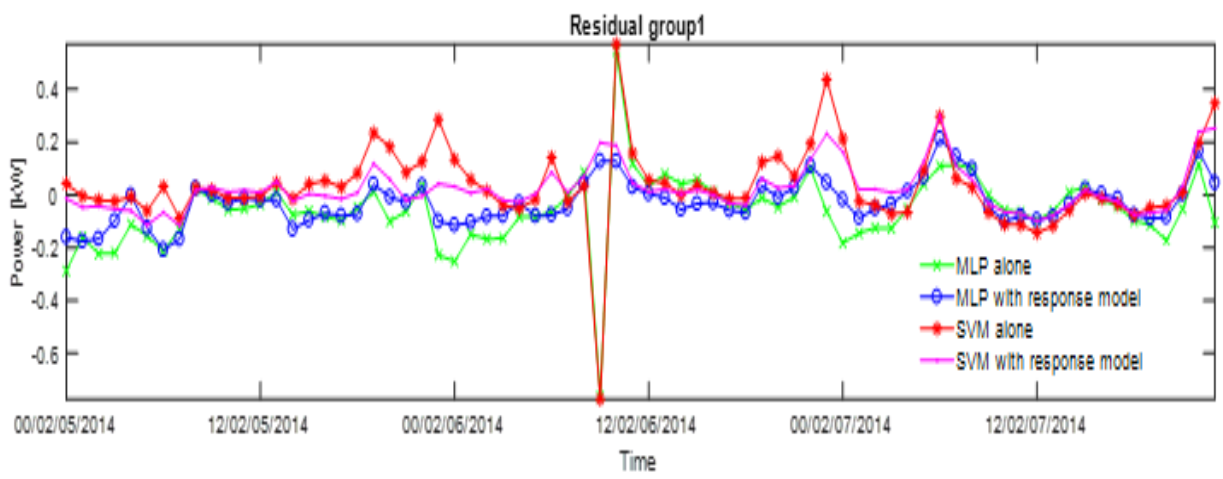
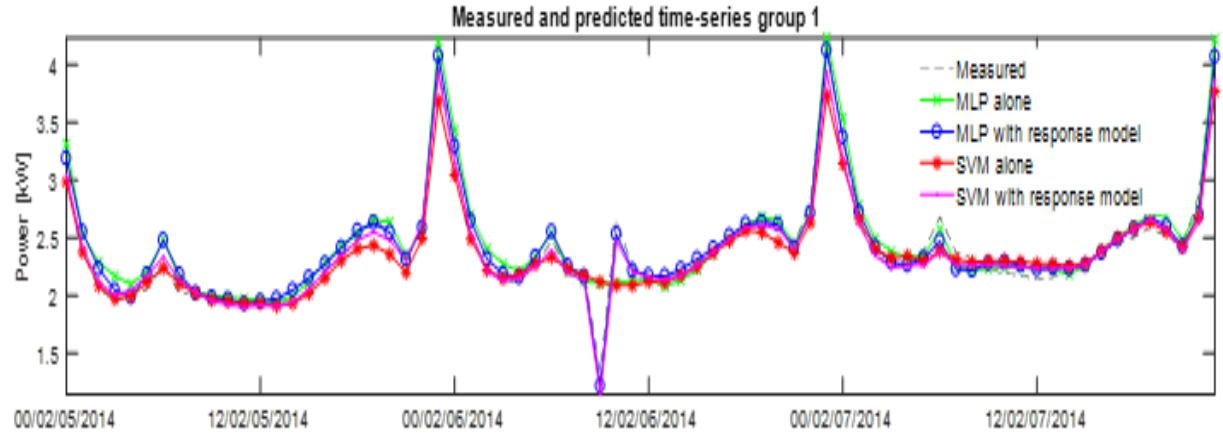
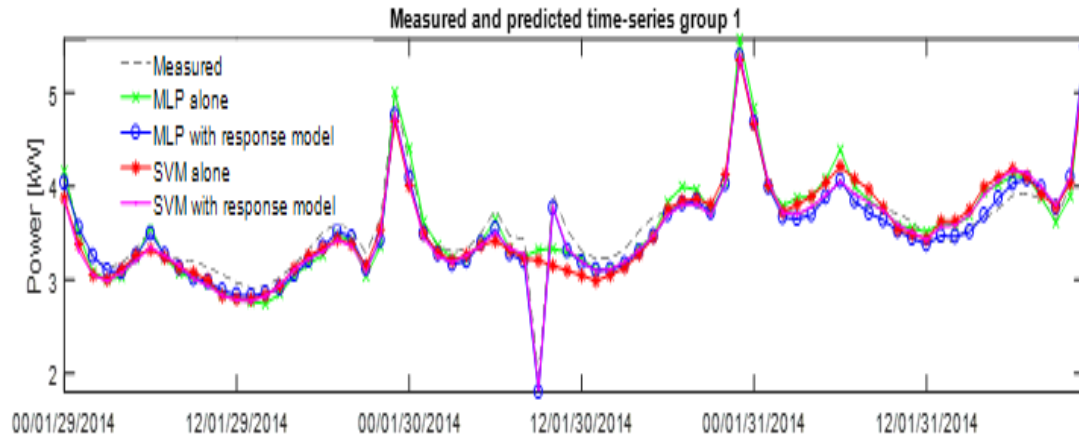
Results in the full storage case

Method \ Normalized RMSE	Identification	Verification
partly physical without response model	0.99105	1.14260
partly physical with response model	0.33606	0.52645
response model and SVM	0.22893	0.36391
response model, SVM and minimum	0.22841	0.34487
response model, SVM and range limit	0.22827	0.34400
SVM	0.17224	0.75300

- In forecasting the dynamically controlled hourly powers, the hybrid approach performed best in the verification.
- The SVM alone forecast very well the identification data but not the verification data. This suggests that the 365 dynamically controlled identification days were not enough for the SVM to generalize the control responses correctly.

Case 2: Emergency load control responses Group 1

loiste



Case 2: emergency load control of partial storage houses case over the two 48 hour periods that include emergency control tests

	RMSE (normalized)			
Method	Group 1	Group 2	Group 3	Group 4
SVM alone	0.2180	0.2784	1.1122	1.1380
MLP alone	0.2037	0.2880	1.3519	1.4536
SVM with response model	0.1162	0.1350	0.5681	0.5820
MLP with response model	0.1126	0.1750	0.6186	0.6493

- The machine learning models could not alone forecast the emergency control responses.
- The forecasts of groups 3 and 4 were inaccurate because the identification data was organized so that the information on load dependence on average load size of the group was lost.

Main lessons learned (1/2)

- **When dynamic load control is applied, response forecasting is necessary for adequate forecasting performance.**
- The partly physically based models forecast the responses more accurately than the machine learning methods alone.
- **Forecasting the residual with the machine learning methods improved the performance of the partly physically based models. Such hybrid model has been the most accurate in all the cases studied so far, also when active demand was not used.**
- **The data driven models more or less completely failed in the presence of active demand, but the hybrid model remained accurate.**

Main lessons learned (2/2)

- The hybrid approach applied is relatively easy to understand and update.
- The main challenge with hybrid approaches is that good knowledge of all the component methods is needed.
- Other hybrid combinations should be developed, analysed and compared.
- **For reaching best performance the data driven models such as machine learning methods and new load profiling approaches need much more identification data than partly physically based models or such hybrid models that include physically based sub-models.**
- **Nonlinear optimal control of residential houses with new energy resources is feasible and finds better solutions than the linear methods.**



Next project steps

- forecasting the total power of the distribution area with 3 minute time resolution, when dynamic load control is applied
 - first study done, second study ongoing
- analysis and development of criteria for the performance of load forecasting
- including the novel load profiles in the hybrid model

Needs for further research

- other hybridization methods in AD forecasting,
- on-line implementation and field testing of the response forecasting,
- field tests in cold temperatures in order to fill in the remaining gaps in the identification and verification data,
- utilization of the baseline forecasts in the markets for AD, and
- estimating confidence intervals for the forecasts
- new application for hybrid models

Deployment prospects

- Accurate short term forecasts in the presence of AD are increasingly critical for the competitive electricity market actors (customers, electricity retailers, flexibility aggregators, etc.)
- Also the grid companies (DSOs and TSOs) increasingly need accurate short term response forecasts.
- The existing state of the art methods in the business are inadequate when AD is applied in large scale. The forecasts developed in the project are accurate also in this case.
- The forecasts provide both the baseline and the response. If the baseline is accepted for market purposes, AD can participate more easily.
- Accurate forecasts can, in some cases, be used instead of expensive reliable real time measurements.
- For residential houses with new energy resources non-linear optimal control gives substantial benefits compared to linear methods.

Thank you for attention

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This research is a part of project Response that is funded by the Academy of Finland.

Presented by Anna Kulmala, anna.kulmala@vtt.fi

Additional slides

- Results and publications, 4 slides
- Relevance to the society

Results and publications of the project Response so far (1/4)

- **Automatic optimization of the structure of the machine learning models enabled model development, comparison and maintenance**

H. Niska, P. Koponen, A. Mutanen, “Evolving smart meter data driven model for short-term forecasting of electric loads”. *IEEE 10th International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)*, Singapore, 2015, 6 p.

- **Overview of the background provided by project SGEM regarding the developments of the utilisation of smart metering data**

A. Mutanen, H. Niska, P. Järventausta, “Mining Smart Meter Data – Case Finland”, CIREC workshop, Helsinki, 2016, 4 p.

Results and publications of the project Response so far (2/4)

- **A hybrid model for forecasting aggregated dynamically controlled electrical storage heating houses. The residual of partly physically based models is forecast with machine learning (SVM). This hybrid model outperformed other methods such as the use of the component methods separately.**
 - P. Koponen, H. Niska, “Hybrid Model for Short-Term Forecasting of Loads and Load Control Responses”, IEEE PES ISGT Europe conference, 2016, 6 p.
 - P. Koponen, H. Niska, R. Huusko, “Improving the performance of machine learning models by integrating partly physical control response models in short-term forecasting of aggregated power system loads”. ITISE 2017, 12p.
 - P. Koponen, H. Niska, R. Huusko, “Combining Machine learning Models with Partly Physical Control Response Models for Short Term Forecasting of Aggregated Loads”, paper submitted to PSCC 2018, 7 p.

Results and publications of the project Response so far (3/4)

- **Nonlinear optimal control of price controlled small houses**
 - P. Koponen, R. Pasonen, A. Löf, " Analysis of optimal dynamic price control of heat pump houses with solar power", CIRED workshop, Helsinki, 2016, 4 p.
 - P. Koponen, R. Pasonen, A. Löf, " Nonlinear optimal control of the responses of residential small houses with new energy resources ", CIRED conference, Glasgow, 2017, 5 p.
- **Simulation model for assessing profitability of battery storage for small customers**
 - Koskela J., Rautiainen A., Järventausta P., Utilization Possibilities of Electrical Energy Storages in Households' Energy Management in Finland. International Review of Electrical Engineering (IREE), Feb 2017, p. 607-617

Results and publications of the project Response so far (4/4)

- **Novel methods for load modeling using AMR measurements**

- M. Nurmiranta, Data driven load modeling and customer behavior change detection. M.Sc. Thesis, TUT, 2017A.
- Mutanen, Improving electricity distribution system state estimation with AMR-based load profiles. Manuscript of dissertation under pre-examination, TUT, autumn 2017

- **Project situation overview**

- P. Koponen, S. Hänninen, A. Mutanen, A. Rautiainen, J. Koskela, H. Koivisto, Pertti Järventausta, H. Niska, M. Kolehmainen, “Improved Modelling of Electric Loads for Enabling Demand Response by Applying Physical and Data-Driven Models, project RESPONSE”, paper submitted to IEEE ENERGYCON 2018. 6 p.

Relevance of this study for the society

- There is very little energy storage in power systems so accurate balancing of generation and consumption is critical for the operation.
- Power system load forecasting is a very much studied and published area.
- Penetration of variable generation increases => need for balancing power increases => balancing using only or mainly the big power plants increases costs and emissions thus eventually cancelling the benefits from renewable generation => It is necessary to increase the use of demand side flexibility or active demand (AD) for balancing.
- One of the main barriers for high AD penetration is that the energy industry uses the mainstream forecasting methods and these completely fail in the presence of AD. Other main barriers are related to market structures and grid regulation.
- The approach developed in the project provides accurate load forecasts also in the presence of AD.