Energy Efficiency in a Mobile World

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Abstract The Danish path to a sustainable energy system focuses on increasing energy efficiency and flexible consumption via smart grid technologies. Information and communication technology is fundamental for achieving these goals by enabling among others new methods and systems for data collection and decision support. This book chapter covers new data collection options exemplified in the concrete case of a living lab for smart grid technologies. Furthermore, the chapter covers the use of visualisation to design decision support for such collected data. We formulate energy management based on energy data as a visualisation problem in the nested model for information visualisation. We prototype a visualisation tool chain to produce a rich set of visualisations based on energy data from five commercial and industrial buildings. Finally, we present qualitative study results for the value of visualisations as an analytical tool. Building on the results we identify important information needs for users of data analysis tools.

1 Introduction

The Danish path to a more sustainable energy system depends on new methods and technologies for increasing the energy efficiency and flexibility of consumption to handle the variable production from renewable energy sources. The Smart Grid Strategy published by The Danish Ministry of Climate and Energy from 2013

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(KEB 2013) details these needs and requested efforts whereby Denmark plans to have a 100 % renewable energy system in 2050. Denmark was one of the first nations to focus on a diversified energy mix, promoting renewables and energy efficiency. Consequently, in 2009 the Danish system already exhibited 18.5 % of intermittent renewable generation (mostly wind power) (Brandstatt et al. 2012). Denmark has a tradition of consumer involvement via municipal and consumer-owned network operators. With its history of bottom-up approaches, the targeted smart grid concept aims to decentralize responsibilities in the system and to equally incorporate demand side and generation resources (Brandstatt et al. 2012). Denmarks smart grid efforts focus on the integration of renewable energy sources, expansion of transmission and distribution networks, active customer participation, advances in information and communication technologies, markets and pioneering concepts of system control and operation in the Danish power system (Zhao et al. 2009). To realize the goal in 2050 the Danish strategies outline a focus on energy efficiency to decrease the total loads and flexibility through out the energy system.

Information and communication technology is a fundamental technology for these developments by enabling new methods and systems for data collection and decision support. Data collection is enabled among others by developments in pervasive and mobile computing providing new modalities and concepts for gathering sensor information about energy consumption and occupant behavior. For instance, energy consumption for individual equipment (Weiss et al. 2012) or temporal-spatial data about humans (Ruiz et al. 2014). For the development of new data processing methods and decision support options it is important to experiment with new options for data collection. One approach is the living lab approach collecting data in situ about buildings, occupant and devices.

Decision support can build on new methods for data mining of collected data or data visualisation to enable data analytics and feedback tools. Buildings account for approximately 40 % of the total energy consumption in Denmark (DEA 2015) and is therefore very important to consider in these efforts. To increase the energy efficiency and decrease consumption of buildings it is important to improve decision support tools with analytical capabilities. In this chapter we focus on electricity consumption which represents often more than fifty percent of the energy consumption in commercial and industry buildings. Surveys of existing energy information systems for buildings report that the systems are limited in their visualisation capabilities and focus on details rather than creating summarizing analytical visualisations of the data (Granderson et al. 2009). Recent studies also report that more advanced data processing tools are underutilized by building energy managers (Granderson et al. 2011). Furthermore, recent commercial efforts to introduce visualisation into commercial tools have so far not been evaluated in terms of their value to domain experts by the research community. The research community has for this domain so far mainly considered visualisation in terms of feedback displays in residential settings (Costanza et al. 2012; Froehlich et al. 2010), detached visualisations of processed data (Jung et al. 2013) or as cases in a design process (Goodwin et al. 2013). Therefore, studies of visualisation on sensing data for commercial and industry buildings are lacking. Both to understand the value of visualisations and the information needs of domain experts not matched by existing pervasive sensing systems.

This chapter provides the following two contributions:

- Present a living lab setting focusing on the collection of rich energy data sets covering renewable energy sources, commercial and industrial buildings and their occupants.
- We formulate energy management based on energy data as a visualisation problem in the nested model for information visualisation. We prototype a visualisation tool chain to produce a rich set of visualisations based on energy data from five commercial and industrial buildings. Finally, we present qualitative study results for the value of visualisations as an analytical tool. Building on the results we identify important information needs for users of data analysis tools.

2 Data Collection in a Smart Grid Living Lab

To stimulate data collection efforts for energy data one approach build on the construction of a living lab. The Green Tech Center Micro Grid Living Lab focuses on the collection of rich energy data sets covering renewable energy sources, commercial and industrial buildings and their occupants.

The Green Tech Center Micro Grid Living Lab is located in Vejle, Denmark, comprising three main buildings, a geothermal platform, a storage platform, a wind turbine and a solar platform with solar panels. The 3-storey building includes a 3500 m^2 area with a commercial Living Lab and various demonstration spaces equipped with different smart energy solutions. In addition an energy guild of nearby companies have been formed. The guild has been established with the goal to foster improvements in energy efficiency in commercial and industry buildings. Together with the guild members we installed a digital metering infrastructure to collect a rich data set of electricity consumption and environmental data. The denseness of submetering differ over the companies from whole building consumption of electricity up to 109 submetered points per building. The temporal granularity of the measurements is one measurement per minute and our repository contains readings for more than a year. The companies can access their data using a web portal. Two energy advisors from a local utility company and a private energy consultancy company, respectively, are associated with the energy guild to assist the companies with their energy efficiency efforts. The energy data from the living lab is also available for other partners via http://data.greentechcenter.dk.

3 Information Visualisation for Sensing Data

Information visualisation hold the potential to create new means for extracting knowledge from sensor data. Today model-based and machine-learning (Rollins and Banerjee 2014; Jung et al. 2013; Hasenfratz et al. 2014) driven approaches are often used in sensing data processing tools. In comparison, information visualisation applies to contexts where domain tasks can only be fuzzy defined (Sedlmair et al. 2012) which makes it hard to apply algorithmic tools. For the study of information visualisation in this context we follow the theoretical model for visualisation research proposed by Munzner (2009). They propose a nested model for visualisation research that nest the four levels of: domain characterisation, data types and operations, and visual encoding and algorithms. Domain characterisation is the description of the domain tasks of users in the target domain. The next level is a mapping of these into operations and data types. The third level is the design of visual encodings and interactions to support those operations, and the innermost fourth level is the algorithms to carry out that design automatically and efficiently (Munzner 2009). In this work we focus on the two outermost levels and the visual encoding which is the most relevant parts for establishing early visualisations for domain experts.

We propose for the visualisation-driven approach to follow a problem-driven visualisation research approach (Sedlmair et al. 2012) which apply relevant methods to inform and validate visualisation work. This includes for our case study literature review, semi-structured interviews, data-driving evaluation of visualisations and observation. The selection of methods provide relevant information to all the considered levels of the nested model (Munzner 2009). Literature review focuses on existing case studies and guidelines for energy management. Semi-structured interviews for understanding domain problems and tasks using open ended questions. Observation for understanding the particular building and places that the building energy managers work in and their options for energy management. Data-driven evaluation of visualisations to collect domain expert's opinion on data types, operations and visual encodings. For a comprehensive discussion of the different types of visualisation methodology we refer the reader to Sedlmair et al. (2012).

4 Case Study on Energy Management

As a case study we consider the improvement of energy management tools with energy data for commercial and industry buildings. To involve domain experts we ran the case with members of an energy guild placed in the Danish city of Vejle (ENE 2015). Our study ran together with five companies and the two energy advisors. The study was conducted by contacting the companies through the person listed as the contact person for the energy guild. A meeting was arranged that included an interview part, visualisation evaluation and observations as part of a

Table 1 Listing of company and interviewee details

	Company A	Company B	Company C	Company D	Company E
Company domain	Office Hotel	Coldstore	Conservation	Conference Hotel	Public Institution
Largest consumption types	Ventilation and Lighting	Cooling	Ventilation and Climate Control	Kitchen and Lighting	Ventilation and Lighting
Interviewees (energy efficiency experience)	Building Administrator (high)	Chief Engineer (high)	Manager and Administrator (low)	Building Administrator (moderate)	Two Chief Engineers (high)
Recent energy efficiency initiatives	New energy efficient building	Optimization of equipment and replacement of inefficient equipment	Optimization of existing equipment and new energy efficient facilities	Optimization of existing equipment and replacement of inefficient equipment	Optimization of equipment and installation of more efficient equipment
Yearly consumption	MWh	GWh	MWh	MWh	MWh

facility tour. As we ran the study with members of the energy guild the companies are biased by having expressed interest in energy efficiency and the results should be judged in this light. The meetings with the two energy advisors included an interview focusing on the role of an advisor and visualisation evaluation with data from the companies. Table 1 lists the details for each of the companies which are selected to differ both in company domain, main consumption types, experience with energy efficiency and amount of yearly consumption. Interviews and evaluations were recorded and pictures were taken to document evaluations and observations at the facilities. The material was afterwards transcripted and coded to identify important topics which was the basis for the presented analysis results.

4.1 Domain Characterisation

Visualisation methodology prescribes a domain characterisation as the first element of developing visualisations and is a contribution in itself (Munzner 2009). As no domain characterisation has been published for energy management in the visualisation community, we will provide one with a focus on tasks relevant to pervasive sensing. To characterise the domain problems and tasks, we combine three sources of information. Firstly, the recent ISO 50001 standard for energy management (Eccleston et al. 2011), case studies of energy information systems and semi-structured interviews to validate the characterisation in the energy guild context. The recent ISO 50001 standard (Eccleston et al. 2011) outlines a number of tasks to be performed by energy managers. We analysed the standard and identified five domain tasks (listed in Fig. 1) prescribed by the standard that focus on analysis

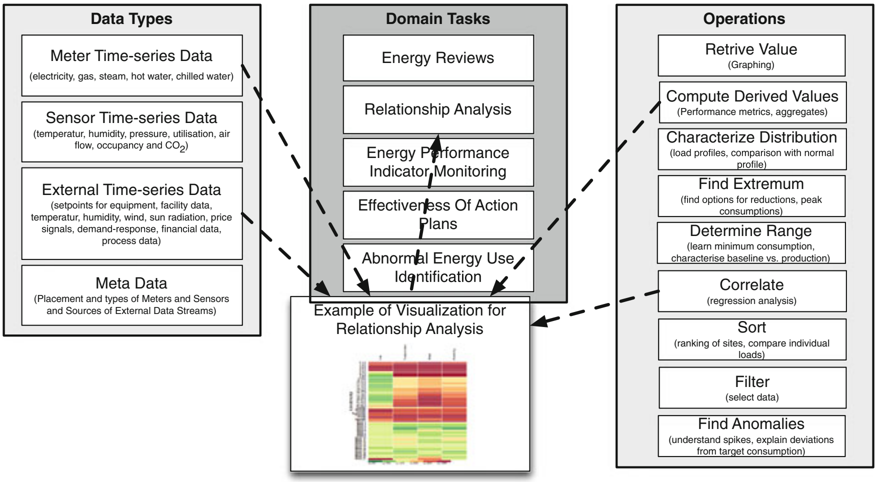

Fig. 1 Domain characterisation, data types and operations

of energy data and therefore possibly supported by visualisation: Firstly, *energy reviews* to identify significant energy use and options for optimization. Secondly, *relationship analysis* to characterize factors that affect energy use, e.g., environmental conditions or production volume. Thirdly, *energy performance indicator monitoring* to track company defined indicators, e.g., reduction targets defined in comparison to a baseline or normalized indicators compared among different buildings or company sites. Fourthly, *abnormal energy use identification* due to faulty equipment or overuse. Fifthly, monitoring the *effectiveness of action plans* including plans for reductions by increased awareness of energy use among staff and installation of more energy efficient equipment.

Granderson et al. (2011) present case studies of energy information systems covering the four large organisations: UC Merced, Sysco, Wal-Mart and UC Berkeley. In the following we analyse if the above five tasks cover the presented case studies. In the case studies, *energy reviews* were mentioned in three out of four cases with UC Merced as the exception due to newly build facilities. *Relationship analysis* is mentioned by all cases except again UC Merced. However, in several of the cases the reported analysis activities are based on intuition from graph plots rather than based on extensive statistical analysis. *Energy performance indicator monitoring* was reported in all cases, for some only comparing the performance over time and for others extensive ranking over the whole building portfolio. *Abnormal energy use identification* was also performed in all cases but the temporal span differ mainly due to staffing restrictions from daily to monthly tracking. Monitoring the *effectiveness of action plans* were also mentioned in all cases but it varied if the activity is described as a short term task on a per action basis or more systematically organized. The cases did not report other significant activities not covered by the tasks described above.

In our study we asked interviewees what the main tasks are for performing energy management. As an underlying issue most companies mentioned that energy management tasks compared to business tasks are running as secondary tasks on an ad hoc basis. For *energy reviews* all company interviewees mentioned concrete activities including: (i) using digitally metered data to understand the breakdown of their consumption. Some had added additional submetering to help break down the consumption into individual loads. Others had tried to manually turn on and off equipment to understand each equipment's impact on the overall consumption; (ii) making detailed analysis of equipment to understand the consumption impact of setpoints; (iii) producing reports from the web portal to provide data to other people in the organisation. For *energy performance indicator monitoring* only company B had made efforts to track key performance indicators more regularly where they had normalized the consumption in regards to production data and environmental data. For *relationship analysis* again only company B had put in effort to understand the relationship between setpoints, outside temperature and energy consumption using scatter plots and linear regression. For *abnormal energy use identification* the participants mentioned that they had used the web portal with live access to their consumption data to follow the consumption on an ad hoc basis to notice deviations. For monitoring the *effectiveness of action plans* most of the companies had compared existing equipment to new equipment on the market to evaluate options for increasing efficiency by replacing equipment. Company B and C had also performed analysis of small experiments with setpoints and after the installation of new equipment quantified the returns. The interviews with the energy advisors generally confirmed that the above domain characterisation captured the main tasks of energy management. Therefore the different sources of information support that the five tasks (listed in Fig. 1) is a fair description of the main tasks of energy management in regards to data analysis.

4.2 Data and Operations

The next level of the nested model is data and operations. Our efforts are informed by existing literature including the case study of Granderson et al. (2011) and their earlier report (Granderson et al. 2009) analysing the data types and operations of energy information systems and information from the interviews. Generally data relevant to energy management are time series of different kinds of physical information. We analysed both the data types mentioned in the case studies of Granderson et al. (2011) and the ones mentioned by our interviewees. Figure 1 lists the identified of types of data relevant to consider when analysing energy data.

Taxonomies have been proposed that describe the low-level operations of analytical activities. We follow the taxonomy proposed by Amar et al. (2005), which define the following low-level operations: retrieve value, filter, compute derived value, find extremum, sort, determine range, characterize distribution, find anomalies, cluster and correlate. However, many domain tasks are compound tasks mapping to several of such low-level operations, e.g., it is very common that domain tasks include retrieve values or computing a derived value. We have listed these operations including examples in Fig. 1. Given that we have analysed domain tasks, data types and operations designing an information visualisation for a specific domain tasks should consists of a mapping to relevant data and operations as illustrated by the example in Fig. 1.

5 Visualisations for Domain Experts

Given the list of identified domain tasks, data types and operations, there are many different options for applying information visualisation. Here we study a subset of these combinations. In this work we focus on the visual encoding and leave interaction design for future work.

We choose to focus on the tasks of *energy reviews*, *relationship analysis* and *abnormal energy use*. Firstly, these are central analytical activities and, secondly, the two remaining tasks can not be implemented in visualisations based on company data without previous interaction with the companies to establish performance indicators and running actions plans. Therefore the remaining two tasks are left for follow-up work. Figure 2 gives an overview of the tasks, data types and visualisation forms designed for the study. The shown visualisations are generated using electricity data from *Company A*. In the following we will refer to the individual visualisations by (X) where X refers to the alphabetic labels in Fig. 2. In regards to the data types listed in Fig. 1 when designing the visual encodings the work was restricted by the available data sources from the companies.

Existing Tool: As the basis of our investigations we took the current web portal available to the members of the energy guild. The portal uses bar charts as the basic visualisation form marked (K) in Fig. 2. Selection mechanisms allow the filtering of data for metering points, periods of time and aggregation levels, e.g., hourly, daily, weekly or monthly. Furthermore, the web portal also provides the ability to extract reports that include measurements as totals listed in tables and pie charts marked as (L) in Fig. 2.

Data Processing Chain: For preparing the visualisations we implemented a data processing chain as shown in Fig. 3. As the first step electricity consumption readings for all submetered loads in the five companies are imported as JSON data (1). The visualisations shown to the interviewees were based on data from January to May 2014. External data is imported in our case weather readings of temperature, humidity and wind speed as JSON data from the REST API of openweathermap.org for the city of Vejle (2). Data is then processed to handle missing data by interpolation and calculate additional model-based time-series in our case a gross estimate of the sun radiation as the hours of sun calculated using a sunset model (Sun 2015) (3). Afterwards, we apply the multichannel weekly model of Braga et al. (2013) who propose to aggregate electricity consumption into a multichannel structure where each hour of the week is represented as a separate channel (4).

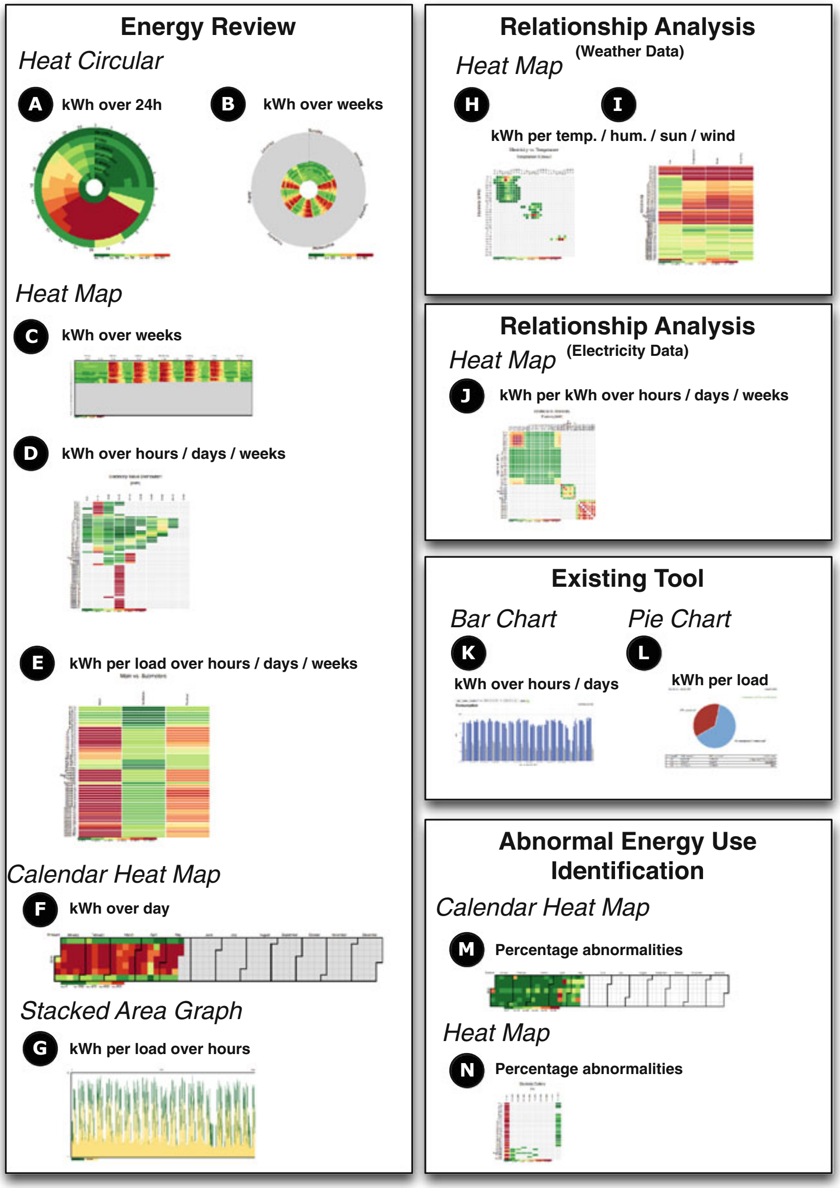

Fig. 2 Summarizing visualisations for domain experts

The readings of each channel is then readings of different weeks for the same hour of the week. Different operators can then be applied to the readings of a channel, e.g., aggregate them by summary statistical operators to compute the mean, minimum, maximum, distribution or standard deviation. For the relationship analysis

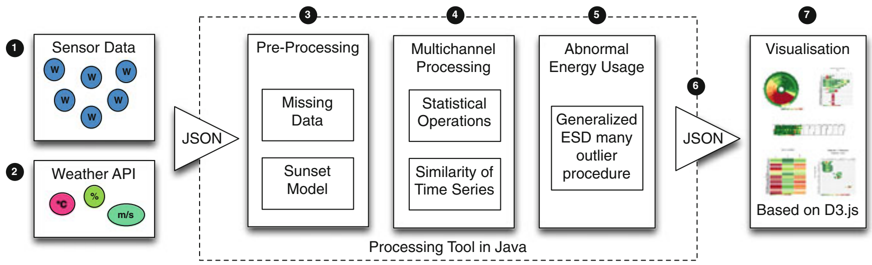

Fig. 3 Processing chain for visualisations

visualisations we compute the similarity of two time-series by, firstly, applying a mean standard deviation normalisation. Finally, we compute the similarity of the normalized time-series using dynamic time warping which can compute a similarity metric for time-series as the cost of the minimum-distance of an optimal alignment.

To provide identification of abnormal energy use we implemented the algorithm proposed by Seem (2007) for detecting abnormal energy use and applied it per channel for the multichannel weekly model (5). The algorithm uses the generalized ESD many-outlier procedure. The algorithm depends on a parameter that specify the likelihood of abnormal energy usage which we set to five percentage to detect only rare cases. The processing chain outputs JSON data for visualisations produced using the D3.js framework. Many of the visualisations were developed taking as outset general templates from the D3.js repository. These were then adapted to the types of data and improved to provide rounded scales, good color schemes and legends to increase usability. The color scheme goes from green over orange to red where green represents low values and red represents high values. The processing chain produces the visualisations with good runtime performance where the only bottleneck for large data sets is the similarity metric based on dynamic time warping which runs in $O(n^2)$.

Energy Reviews: The goal of energy review visualisations is to help domain experts perform energy reviews of commercial and industry buildings. We focus on providing summarizing visualisations to supplement the existing tool focusing on detailed measurements. The *heat circular* visual encoding displays data using a circular clock as a metaphor. This visual encoding allows the folding of time-series data for different time spans across multiple rings to align the same hour of the day or the same day of the week across rings. We developed two visualisations using this visual encoding. Visualisation (A) uses data averaged with the multichannel weekly model and each ring represents a day of the week and the scale of the ring is the 24 h of a day. Visualisation (B) uses hourly readings and each ring represents a week of a year and the scale of the ring covers the hours of the week with markings for each day. The *heat map* visual encoding displays data using a matrix representation as a metaphor. The row and columns represent different dimensions and each entry is color coded to represent the values of the matrix. Visualisation (C) uses hourly readings and folds the time series so each row represents a week. Visualisation (D) uses data averaged with the multichannel weekly model where the first 24 rows represent the hours of a day, the next seven the days of a week and the remaining rows the covered weeks. The columns represent different electrical consumption ranges and each cell represents the percentage of measurements within that hour, day or week and range of consumption. The visualisation thereby shows data in the same visualisation with different aggregation levels. Visualisation (E) uses data averaged with the multichannel weekly model where the first 24 rows represent the hours of a day, the next seven the days of the week and the remaining rows the covered weeks. The first column shows the main load and the following columns the breakdown of the main load into subloads. Each entry is color coded based on the average consumption. The *calendar heat map* visual encoding displays data using a calendar as a metaphor. Each month is represented by a black polygon and each day as a square. The squares are laid out so each row represents a specific day of the week. Visualisation (F) uses this encoding to show the average electricity consumption for each day. The *stacked area graph* visually encodes data as a graph where the measurements from different time series are stacked. Visualisation (G) uses hourly readings of all submeters.

Relationship Analysis: The relationship analysis visualisations are designed to help understand causal relationships between either different data sources or between temporal shifts of the same data. *Heat maps* are used in the following two visualisations. Visualisation (H) uses data for electricity consumption linked with either temperature, humidity, wind or sun radiation. The row dimension represents electricity consumption and contains a scale from the minimum consumption to the maximum consumption repeated three times to represent hourly, daily and weekly data, respectively. The column dimension represents the scale of an external data source again repeated from minimum to maximum three times to represent hourly, daily and weekly data, respectively. Each cell is color coded based on how many hours, days or weeks had an average consumption of this level and an average external data value within the value range of the column. Visualisation (I) uses both electricity consumption data and external data. The row dimension represents temporal information where the first 24 rows represent the hours of a day, the next seven the days of a week and the remaining rows the covered weeks. The columns represent different types of external data. Each cell represents the similarity between the external time series and the electricity consumption computed by dynamic time warping. Visualisation (J) uses only electricity data and a *heat map* visual encoding. The row and column dimensions represent temporal information where the first 24 rows represent the hours of a day, the next seven the days of a week and the remaining rows the covered weeks. Each cell represents the similarity of the electricity consumption for a pair of hours, days or weeks computed by dynamic time warping for time series processed with the multichannel weekly model.

Abnormal Energy Use Identification: The following visualisations are designed to help identify abnormal energy use. Visualisation (M) uses the abnormal use classifications of the Seem (2007) algorithm and a *calendar heat map* visual encoding. Each cell of the calendar heat map represents the percentage of hours of a day classified as abnormal by the algorithm. Visualisation (N) uses the same data but with a *heap map* visual encoding aggregating data using the multichannel weekly model. The row dimension represents temporal information where the first 24 rows represent the hours of a days, the next seven the days of a week and the remaining rows the covered weeks. The column dimension represents the percentage of abnormal classified hours.

6 Evaluating Visualisations

In the following we present study results for the value of the visualisations for domain experts in energy management.

As an example of the visualisations shown to interviewees we discuss the visualisations for Company A shown in Fig. 2. Company A runs an office hotel in a 5500 m^2 large building from 2009 shown in Fig. 4a. To give an impression of the electricity consumption of the building we have included visualisation (A) showing the total consumption of the building in Fig. 4b and the ventilation in particular in Fig. 4c. Analysing the visualisations one can quickly notice the night and day, and week and weekends patterns for the building. Thereby the visualisations provide an easy comprehensible description of the building. For the ventilation one can observe that the maximum consumption stretches into the evening on weekdays and runs shortly at maximum Saturday before noon. If one compares the main consumption and the ventilation consumption it looks like the occupancy related peak

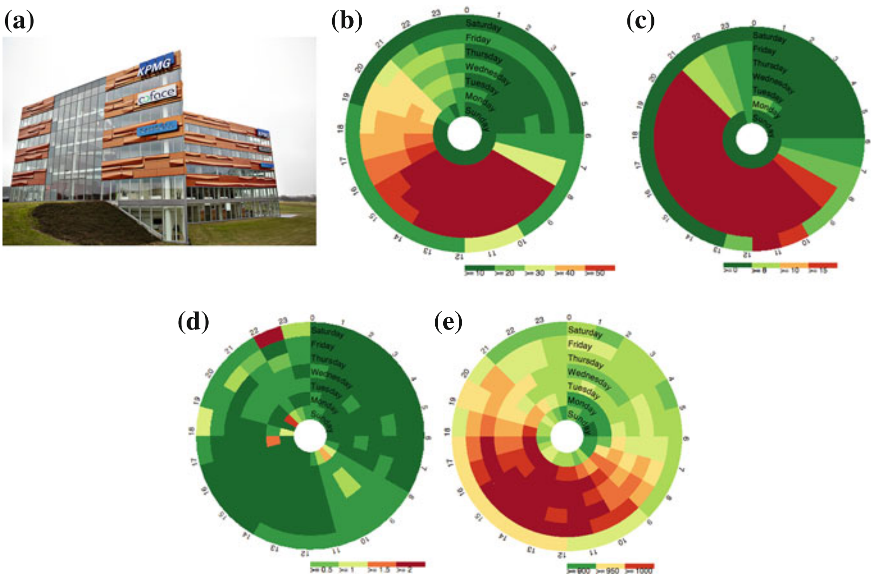

Fig. 4 Visualisation examples for visualisation A. **a** Building of Company A. **b** Total Consumption Company A. **c** Ventilation Company A. **d** UMass Smart* Home. **e** Sutardja Dai Hall at UC Berkeley

load in the building stops much earlier than the ventilation which might represent an option for optimizing the ventilation. The quick overview also makes it easy to recognize different building types, e.g., an office building versus a residential home as shown in Fig. 4d based on data from one of the UMass Smart* Homes. Another aspect is international differences, such as, the midday peak in data shown in Fig. 4e for the Sutardja Dai Hall at UC Berkeley due to air conditioning which is uncommon in Denmark and not present in the Company A building.

For the study we use qualitative methods to gather feedback as this facilitates the gathering of rich feedback from the interviewees based on open-ended questions. The evaluation was conducted by showing the visualisations in a random order on a laptop to interviewees and then at the same time give them a print out of the shown visualisation. The interviewees were then asked to provide comments for each visualisation which were added as post-its and categorise each visualisation into three categories of highly relevant, relevant or irrelevant. The print outs were used to emphasize that the visualisations were not final and thereby encourage the interviewee to provide comments, and to enable them to reorder visualisations if they changed their mind during the session. Figure 5 gives a qualitative overview of how the interviewees placed the visualisations into the different categories. Table 2 lists the analysis results covering both the established practices using the existing tool and the value of summarizing visualisations.

Energy Reviews. During the evaluation several themes emerged in regards to the value of summarizing visualisations in comparison with the established practice at the companies using the existing tool.

Learn consumption: All company interviewees mentioned that using the existing tool they had learned the energy consumption of their building based on the detailed views (K, L). However, the interviewees commented that they had found this process time consuming using the existing tool. When presented with the different visualisations for energy reviews we observed that people generally favoured the summarizing visualisations (A), (C) and (D). The reaction to the visualiations was that the interviewees were able to recognise the information they had gained using the existing tool. For instance, using the visualisations they were able to tell in great

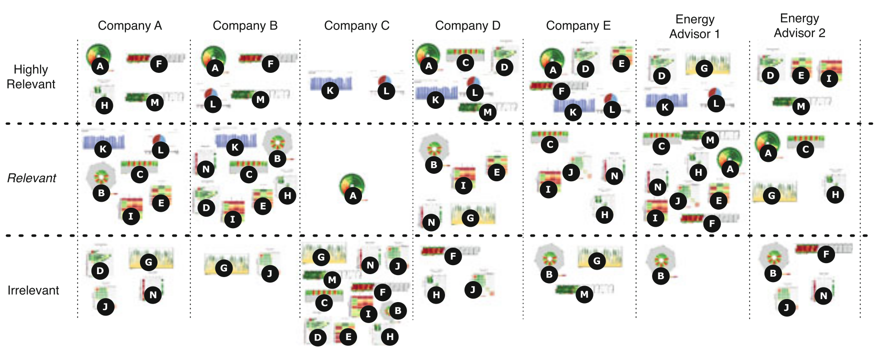

Fig. 5 Categorisation results from the evaluation of prototypes

Table 2 Established practice with comments and the value of summarizing visualisations including the best rated visualisations and comments

	Established practice [Comments]	Value of visualisations (Best Rated) [Comments]
Reviewing energy consumption		
Learn consumption	Numbers + DV [Time demanding]	Positive (A, C, D) [Good overview]
Understand interactions	DV [Time demanding]	*Not considered*
Understand breakdown	DV [Complex process] + Pie Charts [Limited information]	Balanced (E) [Good support for data navigation but easily complex to interpret]
Understand equipment	DV [Time demanding]	Positive (A, C, D) [Good overview]
Stakeholder communication	Numbers and Pie Charts [Too limited]	Positive (A, C, D) [Overview and informative]
Analysing relationships		
Learn dependencies	DV [Intuition rather than facts]	Balanced (H, I) [Multiple factors and missing data]
Handle multiple factors	DV [Intuition] + Linear Regression [Complex]	*Not considered*
Abnormal energy use		
Identification	DV [Ad hoc and complex] and threshold-based alarms [Require tuning]	Balanced (M) [Resolve abnormal usage or abnormal use as events]
Normalization	DV [Intuition]	*Not considered*
Feedback	DV [Not normalized]	*Not considered*

Detailed views (DV) are bar charts of the existing tool

detail what they had learned, e.g., about the variability of consumption, the effect of reconfiguring ventilation and start and end times of production processes. A few observed new things, e.g., Company D was surprised that the consumption varied so much in the evening. Thereby the visualisations enabled the interviewees to recall and communicate the knowledge they had built up. Most interviewees attributed this as a positive aspect of the visualisations and rated them as highly relevant. The two energy analysts generally liked visualisation (D) as they both attributed gave them a better overview and stated that "*The visualisation enabled me to quickly get an overview instead of having to browse through data of 24 weeks.*". Some of the interviewees told that they had personal preferences for preferring a heat circular view compared to a heat map view of the same data.

Understand interactions: Some of the companies had experimented with changing setpoints to learn the impact on the consumption and the consequences for the indoor climate and cooling of goods. However, they commented that these processes had been quite time consuming. As we did not have access to setpoint data, we did not design visualisations for this aspect.

Understand Breakdown: As part of reviewing the electricity consumption, many of the interviewees mentioned the importance of understanding the consumption of individual equipment. Some of the companies mentioned that they would like to get further loads submonitored, e.g., Company B who had installed the most extensive submetering.

Visualisation (E) and (G) were designed to give an overview of the different submonitored equipment. The existing tool uses a pie chart (L) to report the percentage of consumption for different submonitored loads. Several of the interviewees had used the pie charts to get an idea of the overall percentage breakdown. However, for the temporal patterns of consumption they had found this complex to study using the individual detailed views. In connection with visualisation (E) the interviewee from Company B said that it quickly gave him an overview but for (G) he noted that it was too complicated to see anything. Energy advisor 2 viewed displaying submetered data as important and liked (E) but for (G) also noted that it was too complicated but that he would like a version with different zoom levels. Furthermore, it was important that to analyse the behavior of specific equipment to be able to access detailed submetered measurements.

Understand Equipment: All the companies had experimented with switching on and off equipment to learn the impact on the total consumption and life cycle of equipment. They attributed this step as a time consuming process. For some equipment submonitoring had been installed to provide individual measurements. When viewing data for individual equipment people generally favoured the summarizing visualisations (A), (C) and (D). The visualisations also allowed them to spot odd events, e.g., the interviewee of Company A did not understand why they ran ventilation on Saturdays when the building was empty. The advisors liked the overviews but also asked for detailed views as the behavior of some equipment is only observable from minute scale data.

Stakeholder Communication: Several interviewees mentioned that they had used the existing tool to communicate about consumption to other stakeholders, e.g., to management to justify investments in new equipment, to the financial department to document the amount of consumption that is by Danish rules deductible from valued added tax and to other stakeholders to try to influence behavior. For instance, company A had discussed the data with their office renters and also saw it as an important tool to share knowledge in the organisation among both management and technical stakeholders. For the later case the interviewee mentioned that the summarizing visualisations would be important as they show data in a form where also non-technical people can appreciate them.

Analysising Relationships. During the evaluations two themes emerged.

Learn Dependencies: Several of the interviewees commented that learning about dependencies were important because this information could give insights for how to select setpoints to avoid inefficient states of equipment, e.g., for ventilation or to understand the depencies between consumption and influential factors. The factors mentioned included weather data, occupancy and production processes. The companies had tried to learn about these dependencies based on their own intuition as also observed by Granderson et al. (2011).

The visualisations (H) and (I) designed for relationship analysis were only by Company A and Energy advisors 2 rated as highly relevant and else were rated as being relevant. The reason some of the interviewees had reservations for the visualisations were that in several cases the companies' consumption depended on multiple factors and therefore the visualisations designed for only one factor did not show a plausible relationship. Another problem was that other factors than weather drove the electricity consumption, e.g., in the case of company E where the number of hotel and conference guests drove the consumption. A challenge in this connection is that proper analysis might be impossible because data is not collected today or resides in different IT systems. Visualisation (I) had for several of the companies low value as it showed several coincidental relationships. Visualisation (J) designed to analyse the relationship among different times a day, week or year was generally ranked low.

Handle Multiple Factors: For several of the companies the electricity consumption depends on multiple factors. To analyse the factors only company B and the energy advisors had applied different forms of linear regression to the data. They considered such methods complex to apply. In our work we did not design any explicit visualisations for analysing the impact of multiple factors.

Abnormal Energy Use Identification. The visualisations for abnormal energy use identification were designed to provide overviews of abnormal consumption events. Many of the interviewees mentioned that abnormal energy use is an important topic to consider and mentioned examples of cases where they had experienced abnormal consumption and first found out later. Examples mentioned include broken wires, failing thermostats for freezers and failing ventilation that ran at maximum speed.

Identification: Visualisation (M) and (N) were designed to visualize abnormal energy use events. The interviewees generally favored visualisation (M) over (N) as (M) gave them an overview of the different events. However, it was important for several of the interviewees that they would be able to go beyond the overview to see the details to understand what was the issue behind the abnormality. Furthermore, many of them stated that for this information to be really useful it was important to not only provide an overview but to get alarms in real-time so they could act on the information, e.g., for newly serviced equipment to know when it was time for a new service check. Furthermore, it was relevant if the visualisations supported helping to identify the fault as one might have to look into different types of sensor values and status messages for the equipment to find the fault. A situation where one of the advisors saw a special value for the overviews were for recording that an alarm had been appropriately resolved.

Normalization: An issue mentioned when detecting abnormal use was normalization as for some equipment increasing company production would increase consumption but not be a fault. An interviewee also added that it was important to detect abnormal consumption of both low and high consuming equipment because it might be important to handle faulty equipment for other reasons than the impact on total consumption. These aspects were not considered by our visualisations.

Feedback: The visualisations that we evaluated were designed to provide analysis capabilities to stakeholders rather than feedback (Froehlich et al. 2010). However, several of the stakeholders mentioned that in their daily work it was also important to have visualisations that confirmed that daily operations were going as planned. For instance, the interviewee from company B mentioned and showed us during the observations that some of his cooling compressors showed him a smiley when they were operating correctly. Therefore, he would like a similar interface for the rest of his equipment for normal versus abnormal electricity use.

7 From Needs to Better Decision Support

The evaluation results provide both positive and some more balanced results in regards to the value of the developed visualisations. Additionally, the results provide input to themes for improvements of the visualisations in their own right. Table 3 lists evaluations results, visualisation improvement themes and identified

Table 3 Visualisation results and future work coupled with relevant themes

	Visualisation	Themes
Reviewing energy consumption		
Learn consumption	Positive experiences	Learn about temporal patterns of consumptions
Understand interactions	*Open problem*	Learn about causal relationships [Residential: (Rollins and Banerjee 2014)]
Understand equipment	Positive experiences	Learn about equipment temporal patterns
Understand breakdown	Link overview with details	Similarity and ranking of loads, and NILM
Stakeholder communication	Positive experiences	*Not relevant*
Analysing relationships		
Learn dependencies	Multiple factors and missing data	Model dependency using sensing of occupancy behavior (Yang et al. 2014), business activities and environmental conditions
Handle multiple factors	*Open problem*	Disaggregation of multiple factors
Abnormal energy use		
Identification	Resolve abnormal use and events	Detection and modeling of abnormal use (Commercial: Jung et al. 2013)
Normalization	Missing data	Normalize using sensing of occupancy behavior (Yang et al. 2014), business activities and environmental conditions
Feedback	Abnormality feedback	Learn and classify performance

research and development themes for new systems to provide relevant types of information to domain experts. In the following we discuss an example from the list.

For *abnormal energy use* and *identification*, our visualisations were challenged by the domain experts as the most relevant mean. They pointed us to a need for systems to detectabnormal energy use with a low latency in real-time. This is not yet addressed by existing work (Jung et al. 2013). However, our evaluation results also point to an element of fuzziness in the task due to normalisation issues with regards to occupancy behavior and business tasks potentially invalidating solutions without a human in the loop. Additionally, we identified several tasks that could be improved by better system support for fault diagnosis and recording of actions taken to correct issues. These observations highlight the need for better decision support tools and the complexity involved in developing such tools.

8 Conclusions

In this chapter we use a living lab context to argue that using visualisations as a decision-making tool will help improve energy efficiency in commercial and industrial buildings. We presented a case in the domain of energy management for commercial and industry buildings where we applied a visualisation approach in a living lab context. We applied visualisation methodology to develop a domain characterisation, identified relevant data and operations and designed visual encodings for the visualisations. We prototyped a visualisation tool chain to produce these visualisations on a data set and involved domain experts to evaluate the utility of the visualisations. This enabled us to pinpoint working visualisations based on the needs of domain experts, and to identify themes for developing new visualisation tools. We aim to further improve energy management tools for commercial and industrial buildings as these tools can contribute to achieving the Danish sustainability targets.

Points for Discussion

- How does this chapter link new methods to produce new tools to achieve efficiency?
- How can visualisations link what you see and what you can conclude? Can the full complexity of the underlying mechanisms and data be visualized? Should it all be visualized?
- How can we determine what information is useful for an energy manager? Can this change over time or in different settings?

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