An Experimental Investigation on the Comprehension of Electricity Consumption, Generation and Grid Supply Visualization

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ABSTRACT

Energy consumption at the household level has a significant environmental impact. However, it is often difficult for end users to understand this complex topic. Hence, end users need to sight and understand their own energy data by means of appropriate visualizations to achieve a sustainable change towards more efficient energy consumption behavior. By means of an experimental online survey, the comprehension of energy data visualizations with regard to the daily electricity consumption of a multi-person household was surveyed. A total of n = 538 respondents were asked about their comprehension at three levels of difficulty, considering the response duration. The results show that comprehension differs depending on the energy data visualization type and its information density. This work contributes to determine appropriate visualization types to unleash potential for more energy efficient end user behavior.

KEYWORDS

Energy Data, visualization, comprehension, information density, residential energy behaviour, energy efficiency.

INTRODUCTION

In Austria, a considerable part of the energy supply is now generated from renewable energy sources such as hydropower, photovoltaics or wind power. At the private level, the number of photovoltaic systems in particular is increasing. Energy consumption at the household level has a significant impact on the environment. However, it is often difficult for end users to understand this complex issue. This in turn can lead to less willingness to change their own energy consumption behavior. Therefore, end users need to be able to both sight and understand their own energy data in order to bring about a sustainable change towards more efficient energy consumption behavior.

The comprehension of graphics is structured on three levels. The first level deals with reading the data. This means to find certain information in a visualization. This includes, for example, the ability to read the height of a bar in a bar chart or the number of symbols of a certain type

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in a symbol field. At the second level, one should be able to read between the data. The aim is to find relationships in the data that are represented in a visualization. This can be seen, for example, in recognising differences between bars or groups of symbols. The highest level of comprehension of visualizations is the ability to read beyond the data. Here, it is crucial to draw conclusions from the data and to make predictions. This level of understanding is necessary, for example, to predict future trends from line charts or to understand the meaning of scale ranges and scale labels when comparing two graphs [1].

To read information directly from a graph, it is first necessary to understand the concepts of graph design. To process the information read from graphs, comparisons and calculations must be made. Finally, to generalize, predict or identify trends, one must relate the information in the graph to the context of the situation [2].

The comprehension of energy data is related to the willingness to change one's own energy consumption behavior [3]. The type of data visualization in turn influences the extent to which users can understand their electricity consumption. Since different conclusions are drawn about individual consumption depending on the type of presentation, particular attention must be paid to suitable designs and formats in the area of graphic visualization of relevant energy data for end users [4].

Current literature shows that simple bar charts, line charts or pie charts are most commonly used to present energy data [5]. Due to their simplicity, these visualization types lead to a higher level of comprehension among end users and are preferred to unusual or pictorial visualizations [6]. In addition, a visualization of energy data over time in combination with a high temporal resolution argues for the fact that end users can be encouraged to reconsider their household activities, especially with the presentation of peak loads [6]. The use of traditional formats is easier to understand than modern formats. Comparisons of energy consumption within homogeneous periods (hours, days, weeks, years) are common and help end users to identify peak loads [7].

In the context of time series-based energy data visualization, the existing literature often refers to electricity consumption, but not to electricity generation with own photovoltaic systems and electricity supply into the public grid. This leads to the following research question:

Which time series-based data visualization type on electricity consumption, generation and grid supply leads to the highest level of comprehension among end users?

METHODS

The respondents' comprehension of energy data visualizations regarding electricity consumption, electricity generation and grid supply was assessed using an experimental online survey.

Participants

Participants were recruited via various social media channels using snowball sampling. A total of n = 538 respondents took part in the online experiment. The respondents are on average 43.21 years old (SD = 16.61). 55.07% are male and 44.77% are female. One person listed its gender as "diverse". With regard to the highest level of education, 11.37% stated that they had at most an apprenticeship, while 10.12% had completed a secondary vocational school. 32.87% have a school-leaving certificate, the remaining 45.64% have a university degree. Most of the respondents live in a two-person household (39.23%), 13.13% state they live alone. 22.07% live in a three-person household, while households with four or more people are also quite common (25.57%). 20.50% of the respondents have at least one child living in their household (Table 1).

Table 1. Participant sociodemographics

Sociodemographics	M[a]	(SD[b])	%
Gender			
Female			44.77
Male			55.07
Diverse			0.16
Age[c]	43.21	(16.61)	
Education			
Apprenticeship			11.37
Intermediate vocational school			10.12
School-leaving certificate			32.87
University degree			45.64
Housing and floor space[d]			
Flat	78.50	(32.25)	25.93
Single-family house	150.34	(58.96)	61.55
Two-family house or larger	172.57	(101.27)	10.76
Other	140.22	(132.57)	1.76
Household size			
1 person			13.13
2 persons			39.23
3 persons			22.07
4 or more persons			25.57
Children living in household			
None			79.50
1 child			11.56
2 children			7.36
3 or more children			1.58

[a] means, [b] standard deviations, [c] years, [d] m^2, n = 538.

Procedure and measures

Participants were randomly assigned to one of three groups (A, B or C) with different visualization types (VIS) presented (line chart, bar chart, or a rose chart). Within each group, three different levels of information density (INF) were addressed, i.e. i) electricity consumption, ii) electricity consumption and generation, and iii) electricity consumption, generation and grid supply. The stimuli in this 3 (VIS) x 3 (INF) mixed design were created from a one-day time series dataset of a multi-person household and are illustrated in Figure 1.

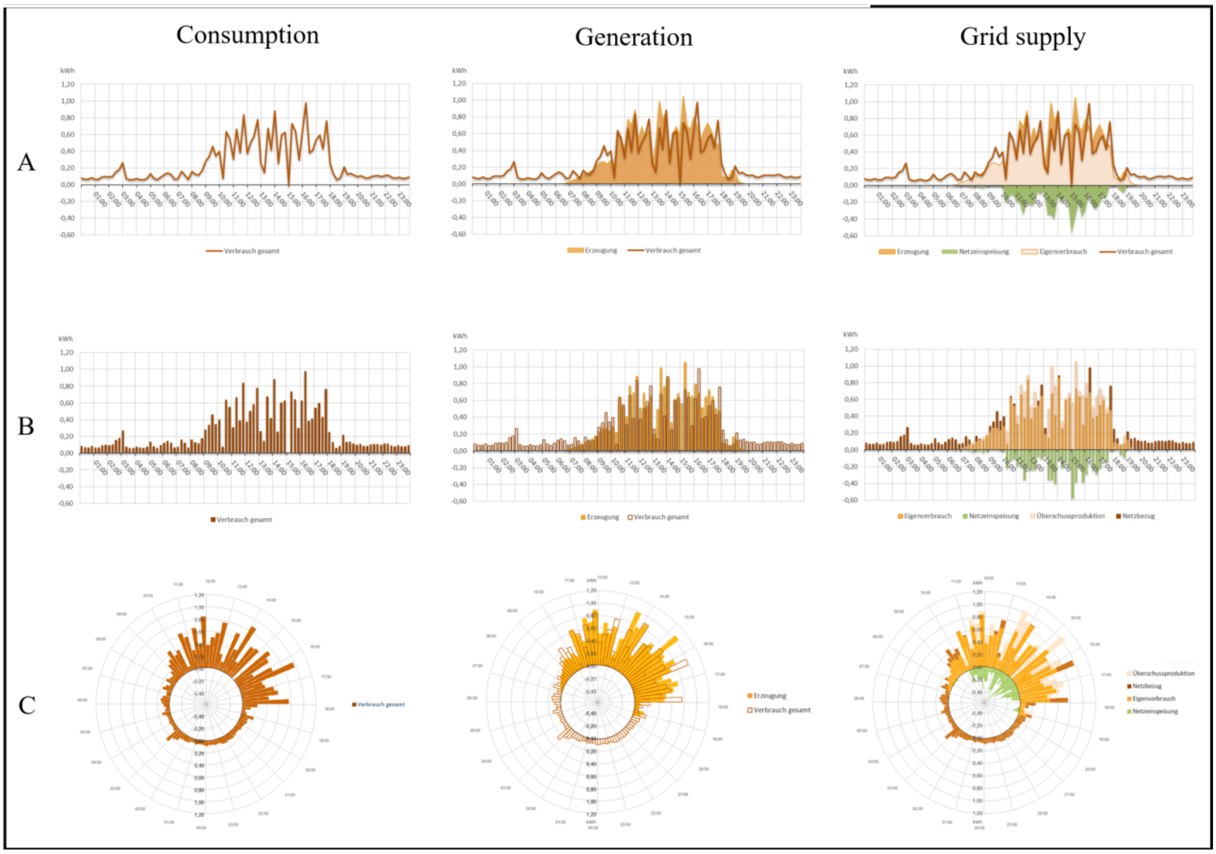

Figure 1. Visualization types and information density level

Comprehension was measured at three levels, i.e., i) read the data, ii) read between the data, and iii) read beyond the data. The questions were developed according to the input of experts in an iterative process. A balanced distribution of open-ended, single-choice, and multiple-choice questions as well as equally distributed comprehension levels were considered. For better practical implementation, two questions per page were asked in the online survey instrument. A list of the comprehension questions, the question type and the comprehension level are stated in Table 2.

Participants could collect scores for each answer. These were made up of the correctness of the answer and the response duration.
For each fully correct answer, a score of 1 could be achieved. Practicable thresholds were set with respect to the open-ended questions (*Q1*: ± 0.10 kWh, *Q4*: ± 15%, *Q6*: ±15 %). If these thresholds were exceeded, a complete score loss for the respective question results. From the correct answer, the scores were linearly reduced until the corresponding threshold. If single-choice questions (*Q2*, *Q5*) were answered falsely, a score of 0 results. The multiple-choice question (*Q3*) allowed to achieve a score of 0.50 for each correct choice (with two correct choices), each incorrect choice led to a score loss of 0.50.
As a second criterion, the response duration was taken into account. For a maximum response time of 45 seconds, a score of 1 resulted; within the range from 45 seconds to 180 seconds, the score was reduced linearly; a response time of more than 180 seconds led to a complete score loss. The score achieved for correctness and duration were finally multiplied with each other, so that a final comprehension score per question resulted. The questions belonging to the respective level of information density were then summarized using the arithmetic mean.

Furthermore, the personal energy affinity was measured as control factor on a 1 = *strongly disagree* to 5 = *strongly agree* scale. Four items were used to comprise the energy affinity scale, e.g., “I know how much electricity is consumed in my household”, and “I can explain the concept of a load profile” ($\alpha = 0.78$).

Table 2. Questions on comprehension, question type and level

	Question	Type	Level
Electricity consumption			
Q1	What is your estimate of consumption between 03.00 am and 03.15 am?	Open-ended[a]	Read the data
Q2	In which period does the consumption peak of the day occur?	Single-choice	Read between the data
Electricity consumption and generation			
Q3	In which of the following periods is always more energy generation than consumption?	Multiple-choice	Read between the data
Q4	Please estimate what percentage of energy consumption is covered by PV generation between 09.00 am and 10.00 am.	Open-ended[b]	Read beyond the data
Electricity consumption, generation and grid supply			
Q5	In which period does the peak of grid supply occur?	Single-choice	Read the data
Q6	Please estimate what percentage of total consumption is self-consumption on that day ("degree of self-sufficiency").	Open-ended[b]	Read beyond the data

[a] response in kWh, [b] response in %.

Analysis

Due to significant outliers, the responses and response durations data is analyzed with robust descriptive methods (medians, interquartile ranges, frequencies). Any differences between the experimental factors VIS and INF were analyzed with the final scores. A repeated measures ANCOVA was used to compare these standardized values for main and interaction effects. The energy affinity scale served as control factor.

RESULTS

Table 3 compares the correct answers with the statistical values of the participants’ answers. The average respondents’ answers to the open-ended questions ($Med_{Q1} = 0.25$, $Med_{Q4} = 66.00$, $Med_{Q6} = 68.00$) are very close to the correct answers (*Q1* = 0.27, *Q4* = 65.14, *Q6* = 73.27). The single-choice questions (*Q2*, *Q5*) were also frequently answered correctly by 87.92% (*Q2*) and 86.12% (*Q5*). The multiple-choice question (*Q3*) was more difficult, only 36.69% of the respondents were able to state both correct choices.

Differences can be observed with respect to the final scores. First of all, the highest scores are achieved at the lowest INF level. For example, visualizations of mere electricity consumption using line charts (M = 0.45, SD = 0.26), bar charts (M = 0.45, SD = 0.25), but also rose charts (M = 0.51, SD = 0.28) are understood comparatively well. Average respondents answered the questions with the lowest INF on merely electricity consumption in a range of 1:04 – 1:07 minutes (IQR 0:39 – 0:50).

Table 3. Comparison of participants' responses and correct answers

	Response		**Correct answer**	
	Med[a]	(IQR[b])	%	Value
F1[c]	0.25	(0.14)		0.27
F2[d]			87.92	4-5 pm
F3[e]			36.69	11-12 am, 3-4 pm
F4[f]	66.00	(25.00)		65.14
F5[d]			86.12	3-4 pm
F6[f]	68.00	(30.00)		73.27

[a] median, [b] interquartile range, [c] response in kWh, [d] single-choice, [e] multiple-choice, [f] response in %.

At the next INF level, the electricity consumption is added to the visualization. Here, the lowest scores are achieved, especially for visualizations using bars (M = 0.22, SD = 0.19) and roses (M = 0.21, SD = 0.20). These questions on electricity consumption and generation took between 1:11 – 1:23 minutes (IQR 0:49 – 1:13). The highest INF also contains information on electricity grid supply. In total, the achieved scores are in turn higher with these visualizations. Both line charts (M = 0.42, SD = 0.27) and bar charts (M = 0.41, SD = 0.24) are similarly well understood at this level. Only the rose chart (M = 0.35, SD = 0.25) leads to a weaker result in this case. For the highest INF, the average respondent needed between 1:04 – 1:12 minutes (IQR 1:01 – 1:06) to answer the questions (Table 4).

Table 4. Comparison of the achieved scores and response durations

	Line chart		Bar chart		Rose chart	
n[a]	164		169		168	
INF	Score[b]	Duration[c]	Score[b]	Duration[c]	Score[b]	Duration[c]
Electricity consumption	0.45 (0.26)	1:04 (0:49)	0.45 (0.25)	1:07 (0:50)	0.51 (0.28)	1:06 (0:39)
Electricity consumption and generation	0.33 (0.24)	1:11 (0:49)	0.22 (0.19)	1:15 (1:00)	0.21 (0.20)	1:23 (1:13)
Electricity consumption, generation and grid supply	0.42 (0.27)	1:06 (1:05)	0.41 (0.24)	1:04 (1:01)	0.35 (0.25)	1:12 (1:06)

[a] sample size, [b] score means within the range [0, 1], standard deviations in brackets, [c] median response durations in minutes, interquartile ranges in brackets.

Results of repeated-measures ANCOVA show that significant, but rather weak differences in VIS ($F(2, 497) = 3.28$, $p = 0.039$, $\eta^2 = 0.013$). On average, line charts are thus somewhat more comprehensible compared to bar charts and rose charts. As already mentioned above, a moderate main effect can be determined with regard to INF ($F(1.96, 972.22) = 29.98$, $p < 0.001$, $\eta^2 = 0.057$). Furthermore, there is an interaction effect between VIZ and INF ($F(3.91, 972.22) = 10.73$, $p < 0.001$, $\eta^2 = 0.041$). Especially at the level of electricity consumption and generation, this weak but still significant effect is most apparent considering the line chart. The rose chart has the highest scores at the lowest INF, whereas it achieves the lowest scores at the highest INF (Figure 2).

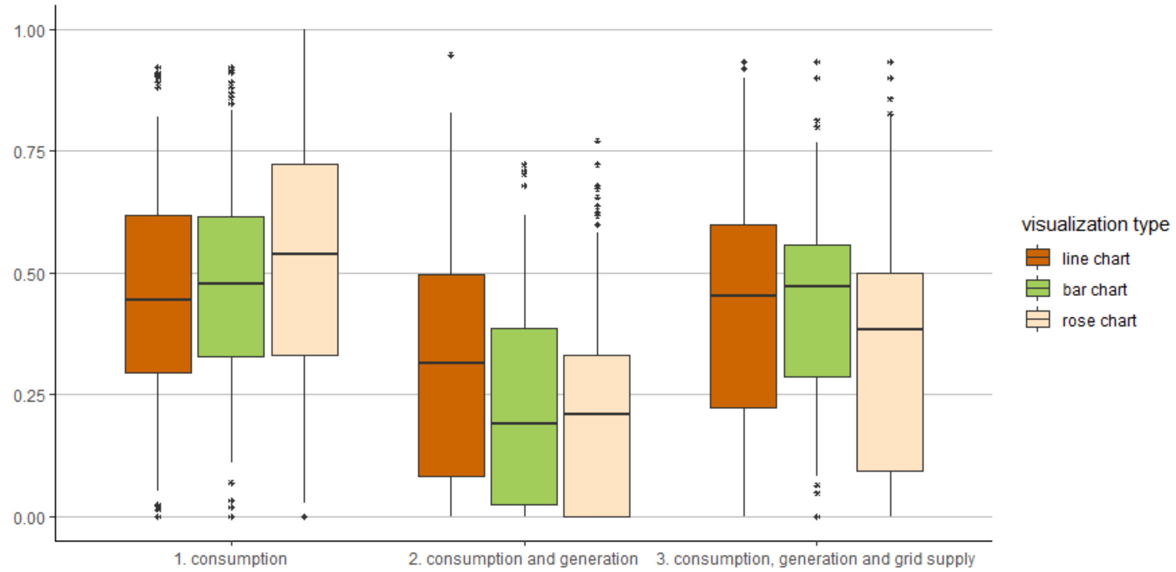

Figure 2. Score distributions by visualization type and information density

The aforementioned effects are already corrected for energy affinity within the ANCOVA ($F(1, 597) = 12.23$, $p = 0.001$, $\eta^2 = 0.024$). Furthermore, understanding different INF levels interacts with energy affinity ($F(1, 96, 972.22) = 4.68$, $p = 0.01$, $\eta^2 = 0.009$). The repeated-measures ANCOVA results are summarized in Table 6.

Table 6. Repeated-measures ANCOVA results

Treatment	df[c]	F	effect[d]
VIS[a]	2.00	3.28^{*}	0.013
INF[b]	1.96	29.98^{***}	0.057
Energy affinity[a]	1.00	12.23^{**}	0.024
Interaction (VIS x INF)[b]	3.91	10.73^{***}	0.041
Interaktion (INF x energy affinity)[b]	1.96	4.68^{*}	0.009

[a] 497 degrees of freedom (error), [b] 972,22 degrees of freedom (error), [c] degrees of freedom (treatment) with Greenhouse-Geisser-correction, [d] 0.010 small effect, 0.060 moderate effect, 0.140 big effect, $^{+}$ p <0,100, * p <0,050, ** p <0,010, *** p <0,001.

CONCLUSION

In this work, the comprehension of visualizations of electricity consumption, generation and grid supply was tested within the framework of an experimental online survey. For this experiment, the visualization types line chart, bar chart and rose chart were used.

In the present work, line and bar charts lead to higher comprehension with increasing information density, which confirms the results of Quispel and Maes [6]. The rose chart, which is rather unusual for energy data visualization, seems to be well comprehensible for illustrations with low complexity. Thus, it could be considered a possible alternative for mere electricity consumption visualization. However, compared to line and bar charts, the rose chart loses comprehensibility with increasing information density.

With regard to the information density of the data visualization, significant differences were found. First, a comparatively high level of comprehension is achieved when looking at the mere power consumption – relatively independent of the visualization type. Second, a clear effect can be detected as soon as additional information – in this case electricity generation – is added to the visualization. Third, a certain learning effect can be derived from the results of the highest comprehension level regarding electricity consumption, generation and grid supply. The subjects were shown the comparatively most complex visualization last.

The results of this work provide valuable insights into how to achieve higher user-friendliness in smart energy management systems for private households and thus create an additional driver for sustainable, efficient energy consumption behavior.

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NOMENCLATURE

ANCOVA … Analysis of covariance
INF … information densitiy
IQR … interquartile range
M … mean
Med … median
n … sample size
SD … standard deviation
VIS … visualization type

REFERENCES

1. Galesic, M. and Garcia-Retamero, R., Graph literacy: a cross-cultural comparison, *Medical decision making: an international journal of the Society for Medical Decision Making,* Vol 31, No. 3, pp 444–457, 2011.
2. Friel, S. N., Curcio, Frances R. and Bright, G. W., Making Sense of Graphs: Critical Factors Influencing Comprehension and Instructional Implications, *Journal for Research in Mathematics Education* Vol. 32, No. 2, p 124, 2001.
3. Fischer, C., Feedback on household electricity consumption: a tool for saving energy?, *Energy Efficiency* Vol. 1, No. 1, pp 79–104, 2008.
4. Herrmann, M.R., Brumby, D.P., Oreszczyn, T. and Gilbert, X.M.P., Does data visualization affect users' understanding of electricity consumption?, *Building Research & Information* Vol. 46, No. 3, pp 238-250, 2017.
5. Grant, W., Energy Data Visualization Requires Additional Approaches to Continue to be Relevant in a World with Greater Low-Carbon Generation, *Frontiers in Energy Research* Vol. 4, No. 33, 2016.

6. Quispel, A. and Maes, A., Would you prefer pie or cupcakes? Preferences for data visualization designs of professionals and laypeople in graphic design. *Journal of Visual Languages and Computing* Vol. 25, pp 107-116, 2014.
7. Murugesan, L. K., Hoda, R. and Salcic, Z., Design criteria for visualization of energy consumption: A systematic literature review, *Sustainable Cities and Society* Vol. 18 pp 1–12, 2015.