Wasted Energy? Illuminating Energy Data with Ontologies

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Abstract—Using Pervasive Computing to reduce energy demand of complex commercial premises is extremely challenging in practice. Yet, this is exactly what is needed to help organisations address climate and decarbonisation targets. Complex and heterogenous data, changing policy and practice, evolving infrastructures and estates, multiple stakeholders, and transient and persistent faults hidden in longitudinal data from thousands of sensors, are just some of the challenges to overcome. In our multi-year experience of working to create software systems to help find energy savings and enable effective policy creation, we have found an important gap that complicates our efforts: missing business context. In this article we contribute our key lessons learned so far; categorising the different types of information missing that need to be captured; and describe how linking this sea of information meaningfully is one of the most important, yet most complicated endeavours in energy management. We offer ontologies as a way to bridge stakeholder domains, and offer unique opportunities for organisations and researchers in Pervasive Sustainability and beyond to create better tools for enabling improved practice and operation in smart energy management.

INTRODUCTION

Globally, billions of building and energy data points are collected each day across the commercial sector. Pervasive Computing has already shown use cases for these data to enable energy interventions,[1] energy sensing,[2] smart home automation,[3] and living laboratories.[4] Tantalisingly, can these data, often already generated already as part of many built infrastructures, help reduce energy demand by increasing efficiency and improving understanding of the link between energy and current practice?

One only has to walk around a typical office building, business park or campus environment, to see what might be termed 'energy waste'. Lights and displays left on in unoccupied rooms, or overnight; poorly regulated overwarm or overcooled buildings; especially with recent shifts to hybrid and home working. But also, and perhaps more profoundly, as infrastructures are laid down and evolve over time, projects and people come and go and layer new energy demanding infrastructures over old, where does all this energy actually go—and is it now 'being wasted'?

Researchers in the Pervasive Computing community have previously urged for more work in sustainability,[5] sparking a surge of publications and workshops.[6] Recent reviews of these efforts since have renewed calls to action,[7] intriguing us to understand energy demand and help develop interventions to reduce energy waste and its associated carbon emissions.

In our work we have sought to investigate how we can find insights for energy savings and organisational change from the energy and smart campus data already gathered in non-domestic settings. While plentiful quantitative data relating to automated metering

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(with work) can be accessed, actually reducing and contextualising energy demand and identifying sites of ‘energy waste’ requires additional quantitative and qualitative data (which we term context) that we do not have. We have found that purely looking at quantitative data does not tell the whole story: events, patterns, and anomalies that may be able to be detected using statistical and computational methods, need to be contextualised to explain such phenomena meaningfully.

Solving this conundrum can enable the building of tools for stakeholders such as energy managers to address smaller issues on the ground, but also have the far-reaching impacts such as implementing or affecting change for policies on the broader scope, we seek.

In this paper we explore how we can bring together a variety of data in a structured manner, to unpack the complexity of commercial organisations and provide insights that connect to business practice and policies, and the rhythms of the commercial organisation. This includes the type of information that is important for energy management—but we would argue *critically rarely recorded*—the storage of such, when linked together, can be utilised to enable new and more effective automated analysis and stakeholder tools. Drawing on specific examples chosen from our long running work in this area, we offer an ‘ontology approach’ that provides a extensible mechanism to help address the technical integration of these data. We showcase this using examples drawn from current work from real-world ongoing commercial case studies. Our contributions are a categorisation of the different types of information we find useful; a presentation of an ontological approach to capture this information; and an outlook of how pervasive researchers can better understand and communicate energy data in relation to commercial settings.

BACKGROUND

As researchers, with expertise in energy, sustainability pervasive computing and HCI, we will openly say that looking at the time-series energy and building data alone is limiting and can be frustrating. While statistical methods often work well with clean or synthetic data, data from sensors deployed in buildings and campuses for perhaps many years presents orders of magnitude more challenge. A statistical ‘anomaly’ that looks interesting as energy waste, might in fact be connected to hardware breakdown, software failure, network reconfiguration, or a one-off event. Incorrect interpretation of these data can lead to ineffective or incorrect changes to future energy management. Perhaps worse still, false conclusions erodes trust in pervasive tools and techniques, or the promise of such, for important stakeholders.

Over many of the authors experience over the last decade or so of engaging with this problem domain, we have seen a variety of energy management systems emerge, be implemented, and get replaced. The authors have collected and analysed data in many different shapes and quantities, from small-scale home qualitative energy intervention studies to large-scale quantitative data hubs comprising billions of data points and spanning several years. Especially in commercial settings, time series data often forms the backbone of energy data analysis.

What is ‘The Data Challenge’?

To elaborate on the problem of data variety, availability, and accessibility, we refer to a relatively recent example. Our largest dataset stems from our analysis of electricity use on a University campus in UK. We gather nearly 60,000 streams of time-series data from the energy and building management systems (approx. 70 million data points per month). One common type of analysis is to compare the night time and day time energy use or the difference between ‘the base load’ energy used even when a building is thought to be unoccupied and the ‘peak load’. Most of the buildings on campus are mixed use, comprising a mix of backroom plant, offices, teaching spaces, shops or accommodation, complicating interpretation. When analysing one of the rarer and simpler to analyse single use buildings recently we found it had an unusually high base load that was even exceeding its peak day time energy consumption. This is extremely unusual. We zoomed in on the raw time series data points and noticed a strange pattern of high consumption cyclic peaks of ten times the normal load level, in regular intervals but only occurring at night (see Figure 1). This pattern was observable for several years suggesting a link to the building’s infrastructure or perhaps linked to regular energy intensive working practices.

Naturally this ‘odd behaviour’ was raising questions. The data stream itself did not tell us the answer, and this pattern was unfamiliar to the stakeholders we spoke to. We could not explain the pattern from any of the historic data, nor typical cycles of energy use we can normally relate to day to day ‘business as usual’. Our first attempt was to contact the building’s manager. We were told that the building was only occupied during normal daytime hours, but that cleaning staff were known to come in ‘after work’. The staff in that building had no explanation for the electricity consump-

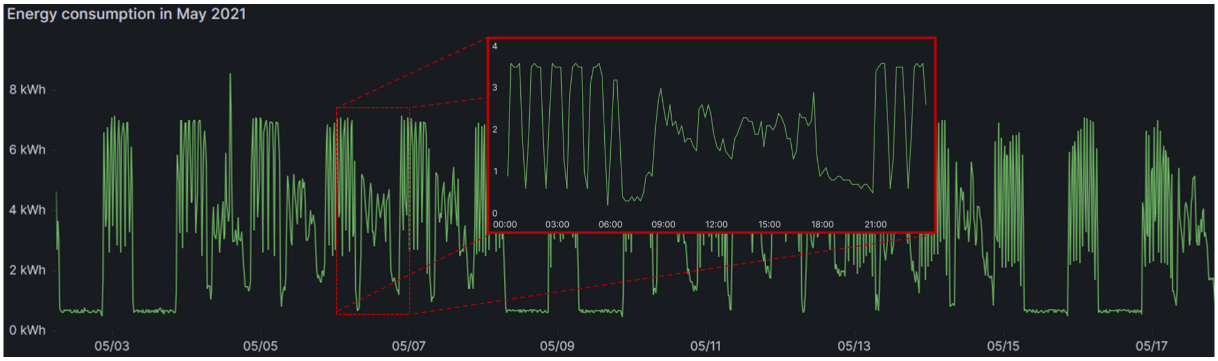

FIGURE 1. Consumption patterns over two weeks in a university campus building, exposing unusually high night time usage (zoomed in view).

tion spikes, and naturally, energy management is not part of their normal daily responsibilities.

As a next step, we contacted the Facility management department, who, equally concerned, launched their own investigation. A technician conjectured that a plant room's hot water storage vessel might have been the cause, as the building required increased water safety monitoring due to its primary use. However, this did not explain the increased night time consumption, as opposed to day time when one would expect water to be actually used. What further complicated the quest was that the timing and recent history before the night time pattern stopped: the expansion of a district heating system replaced the individual building's heating system. It was supposed, the building in question might have had further installation changes in its plant room during this period. Some staff of the University's facility management had recently also changed, which made it harder to recover any further knowledge of these changes, due to 'loss of institutional memory'.

This left us with two significant challenges: First, we did not manage to get a satisfying answer to solve our riddle, the spikes in night time consumption—which have since stopped—remain a mystery. Second, for identifying other past, present, or future anomalies of a similar kind, we need a robust system—or perhaps churlishly, any system—to capture relevant organisational context to explain future events and relate these to regular patterns of energy use. Third, and most importantly, the documentation of this incidence is the result of a lot of specific piecemeal investigative work. The time series data is located in a time series database; the analysis was done using custom written scripts on the researcher's computers, shared and discussed in the University's communication platforms; the communication with the stakeholders was done via email or informally in person. This represents critical information gaps: concerning the information about infrastructure and technology, such as the devices in the plant room and the consumers of electricity, that was not centrally documented. Information about policies such as the switch to district heating, working hours of staff, cleaning staff's access to the building, and potentially other consumers is not centrally documented either. This type of analysis hardly scales given the complexity of even modest built and monitored infrastructures!

Recording and taxonomising these data

We have been exploring how to capture, maintain, and utilise all these forms of data that we have found important. Using ontologies is not a new concept by itself in the realm of energy management; ontologies are an established way of documenting the semantic structure of energy management systems.[8] Their use is not just limited to buildings and organisations of our scope, but has been explored in small-scale use cases such as smart homes[9] up to the scale of smart grids[10] or even entire smart cities.[11] Existing examples within the pervasive community even included first approaches to include contextual information.[12]

TYPES OF ENERGY DATA

To avoid situations like this in the future, we sought to establish a comprehensive database to store relevant but open-ended information of this kind, and where possible capturing this in an ontology that we can then combine to aid our analysis. In our search for such a solution we turned to attention to ontologies, which have been used in many other domains. A strength of ontologies being the ability to link information of various types of data, and express and encode relationships in a repeatable and standardisable way. To illustrate why we believe ontologies are an appropriate or even a good tool for this challenge, we will first present an overview of all types of data we have found to be relevant in energy management settings. Following this we will elaborate on the features of ontologies in general as well as showcase examples of ontologies we have utilised in more detail.

To be able to create such an ontology, we first need to assess what kind of information we find relevant for energy management. We arrived at this list by reviewing and coding our collective notes of past research and ongoing work with partner data in the energy management domain, noting down every type of information that was relevant for stakeholders working on energy decision making, as well as in research projects and interventions. We then mapped all the data types using a card sorting exercise to cluster similar types of information together and identify distinctions between the various categories. These categories were then iterated on through discussions among researchers, until it was concluded that the representation matches the collective experience of energy data in past and present projects.

1) **Time Series Data.** Arguably the most common information that energy analysis focuses on is time series data (TSD), such as from meters that record power consumption at a certain frequency. Depending on the size of infrastructure, technological implementation, and age of building and system this information can be split into more or less detail by being at per-building level, floor level, or even per room in some cases (typically we've found granularity of sensing and data increases in newer buildings and later generations of data logger offer more sophistication in terms of sampling flexibility and power related parameteres they log). The type of information also varies, from power consumption to water, heat, temperature, gas, oil, or other energy-related information. The key element of TSD is that it provides a stream of information with tuples of a timestamp and an associated value at that point in time.
2) **Metadata.** Closely related to TSD, metadata provides information describing the time series data itself or its sources. Examples include unit of measurement, frequency, sensor location, resolution of the logged data, but also descriptive features such as start and end date of reading, number of values, or even semi-automated secondary measures such as mean, variance, or number of missing values. Essentially, metadata is considered to be information that is directly related to a particular time series, but not associated to an individual timestamp.
3) **Post-Processed Data.** Raw time series data may be cleaned or resampled to ease further processing. This includes a cleaned data stream, which is close to the original time series data, but after the removal of outliers. Data gaps may be filled with extrapolated data points or forecasts, or adjusted for normalisation and standards (such as cumulative meter readings turned into rate or respecting multipliers for conversion). This kind of post-processed data might still be a time series data type, but needs metadata, tags, or other identifiers to store information about its origin and alterations made within the data pipeline. The next level of post-analysis data are outputs from algorithms to analyse patterns, such as statistical models, anomaly or changepoint detection, and various types of insights that usually are turned into visualisations. This is the form most commonly seen for energy data, especially by the public. There is no standard for what this type of information looks like, as it can range from a stream similar to the original time series, e.g., for a correlation analysis between energy consumption and weather, which results in another time series. Or might be a single data point, such as the emergence of a single anomaly detected at a point in time.
4) **Timestamped Contextual Data.** In contrast with context-aware computing who's notions of context have been criticised,[13] we consider context as annotation to add meaning to a time series by conveying information about a certain point in time or time range. The most common examples are seasonal patterns relating to business practice such as weekends, working/opening hours, or serving as an explanation for regularly occurring patterns in energy increase or decrease that are normally seen. Another group of examples are explanatory of events either planned or unplannedwhich might cause deviation from 'regular' energy patterns; such as sales promotions, blackouts, or erroneous readings. These are thus non-recurring singular points of context providing a reasoning for sequences of anomalies or even periods of missing data.
5) **Qualitative Contextual Data.** We need to capture and represent qualitative data, such as explanations and narrative illicited from interviews, informal testimony from occupants or other stakeholders, or descriptive information about energy data and its sources not otherwise considered formal metadata. In contrast to the previous examples, this type of data often requires more additional analysis before it can be linked to a time series, but can often shed light on an observed or detected patterns or

anomalies. In some cases, this kind of contextual information even exists *without* any noticeable deviation from the normal patterns of energy use in the TSD. Deployment of a research project, a change in energy management policy, or an intervention to try and implement a 'behaviour change' policy all may actually result in no statistically significant effect. Usually the most complicated bit of work in connecting this type of data to TSD is that it is rarely directly linked to a single point in time. Even if it does, the temporality is often hazy in the minds of the interviewees or stakeholders, unless for the few rare occasions where capturing such information is tied to a documented organisational practice.

6) **Outputs: Reports, Visualisations, and Policy Briefs.** This type of information consists of polished analysis and synthensis as documented outputs. Reports may include results of sophisticated analysis or data visualisations; internal/ external facing reports (e.g. annual or quarterly reports); and policy documents outlining general strategies that can be linked to energy use directly or indirectly (for example, heating policy, changes to air handling for mitigating airbourne viruses). Such data can be important to contextualise TSD or even other qualitative data, and needs further analysis to be directly linked to other types of energy data. Storing the entire record and then analysing it into piecemeal items that can be directly linked to other types of information helps to complete the picture of the energy information.
7) **Hardware and Infrastructure Documentation.** The metadata often explains the time series data origin, but there is sometimes the need for more in-depth information about the hardware, how it is connected, how the data is being captured, and how it all ties together. For the purpose of identifying faults, and especially to distinguish a hardware breakdown from a statistically significant change in energy use that turns into an insightful result, it can be key to have a survey of hardware that is related to all things energy management. Organisations and its energy infrastructure change over time due to change of building use, upgrades, building development, etc. A full survey of all relevant infrastructure, what it powers, and the software pipeline that forms the backend of the energy data logging, helps to paint the full picture and build trust in the data pipeline. Such surveys are expensive and time consuming, so it is more common for this picture to emerge incompletely over time.

AN ONTOLOGICAL MATTER

Ontologies are representations of knowledge or information specific to a domain or subject area. An ontology captures knowledge (concepts), the relationships between concepts, and properties of a concept, in a way that is query-able and is standardised across domains. They are commonly used in the fields of linguistics and biology, but their use is growing in other fields. Whilst formally an ontology represents knowledge within a specific domain, the concept is closely related to the concepts of graphs (the structural concept behind the ontological approach) and linked data (the method for implementing the ontological approach). Whilst an ontology itself is typically used to store knowledge that can be represented by a short string, a number or a boolean, by leveraging the linked data method, knowledge held in all of the types of data discussed above can be captured.

Ontologies come in various concrete forms, depending on the application domain and intended goals. Energy management ontologies commonly follow the format as defined by the OWL Working Group[1]. Although terms vary, for clarity we will use the following terms in the remainder of the paper and explain how we utilised them in our work:

- *Class*—Examples for this can be types of infrastructure ranging from entire buildings to individual meters, but also stakeholders or any other cluster of information or concepts such as units or the concept of an event
- *Literal*—Singular entities of information pertaining to a particular class to provide a narrow definition for capturing a value; examples are numerical size and labels, but also unique identifiers to link to raw information
- *Instance*—A realisation of the class
- *Relationship*—Linking classes, Literals and Instances together; the relationship in-itself provides the context between two elements

We emphasise that this is just one of many possible ways to describe the parts that make up an ontology—there may be as many definitions as ontologies, and there are more extensive discussions of the construction of ontologies as well as their individual components[14]Note we are not necessarily arguing that ontologies are the only way to capture and encode the business context we need to better explore and understand the energy data, or enable computational analysis methods. We also fully expect that not all

[1] https://www.w3.org/OWL/

business context and qualitative information is well suited to these methods, in part due to its socially constructed and fluid nature.[13] In the following, we elaborate on our use of ontologies and how we applied the concept to our projects by pointing to a case study in which ontologies were beneficial to our work. Later on, we will discuss the lessons learned from utilising them in our research.

Case Study: Quick Service Restaurant

A quick service restaurant is a type of restaurant specialising in 'fast food' service. These days typical restaurants specialise in take-away, may have table service and may have a drive-thru facility. In our case study, food is generally deep fried then kept warm. The restaurant is thermally regulated using air conditioning, and has a refrigerated storage facility. Energy management within Quick Service Restaurants (QSR) is key to their profitability. Naturally, there is significant interest in finding issues in the restaurant infrastructure or use of infrastructure that can lead to expensive wastes of energy. For example, deep fat friers or airconditioners left on out of hours or for extended periods. QSRs often experience a high turn over of staff, which can also lead to loss of knowledge about how to use the systems or lack of long term engagement with energy savings automation systems or policies. In this example, by building upon existing ontologies, we show how we can identify and capture information about poor energy management.

Figure 2(a) shows a hierarchy of classes, instances of which represent the monitored equipment in a QSR in our `net0i` ontology. In line with best practice, our ontology extends pre-existing ontologies such as the `DOLCE + DnS Ultralite`[2] (denoted `dul:`) by sub-classing `dul:situation` and `dul:designedArtifact` to fully capture granularity in the types of issue and range of equipment. The relationships and classes that we use to provide context, utilise other ontologies, such as the `OWL Time` ontology[3] (`time:`) for describing temporal concepts and `QUDT`[4] (`qudt:`) for measurement units.

To illustrate the use of these classes and associated ontologies consider the (simplified) representation in Figure 2(c). This shows a fryer, "fryer number 1" (instance #74516, class `net0i:fryer`) with relationships to instances of other classes, which in turn describe its properties. For example, instance #16290 (class `qudt:quantity`) represents information about its electrical power rating and instance #92105 (class `geo:spatialLocation`) information about its physical location.

The issue (instance #57348) has class `net0i:offTooLateSchedulingIssue`. This combined with its `dul:hasConstituent` relationship with "fryer number 1" indicates poor energy management since the fryer has been left on for too long out of hours. The start time of the issue (instance #30984, class `dul:Event`) is the end of the expected operating hours. The end time of the issue (instance #23579, class `dul:Event`) is given by a time interval (instance #61742, class `time:Interval`), with a relationship of `time:hasTimeInstantInside`, indicating that the time at which the fryer was switched off is unknown but between the time it should have been turned off and an end time (instance #39815, class `time:Instant`, relationship `time:isEndedBy`).

In practice the full ontology for QSRs is more complex than this, to allow for the storing of data relating to, for example, multiple QSR sites, one-off events and sales promotions all of which could effect the energy use. The representation of both issues and equipment within the same ontology does however offer multiple benefits, such as being able to uncover new insights beyond the usual quantitative data analysis and automated rule-based evaluation.

DISCUSSION

Documenting the different types of data arising in energy management as well as utilising ontologies to store and link them together has elevated our project work and is already starting to allow us to discover new insights. We believe the lessons learned extend not only to other similar projects in the domain of energy management and applied pervasive computing in smart buildings and environments. The approach provides conceptual clarity which reduces ambiguity of terms; provides a common framework of integrating data from multiple sources effectively. Ontologies can enable portability of algorithms and methods due to semantic interoperability or comparability across sites with different infrastructures. Importantly, codifying some of the business context in this way can also improve our ability to do knowledge discovery using automatic analytics and reasoning.

Putting Energy in Context

In interviews with energy stakeholders as well as in our own research reflections we repeatedly encoun-

[2] https://triplydb.com/odp/dul
[3] https://www.w3.org/TR/owl-time/
[4] https://fairsharing.org/FAIRsharing.d3pqw7

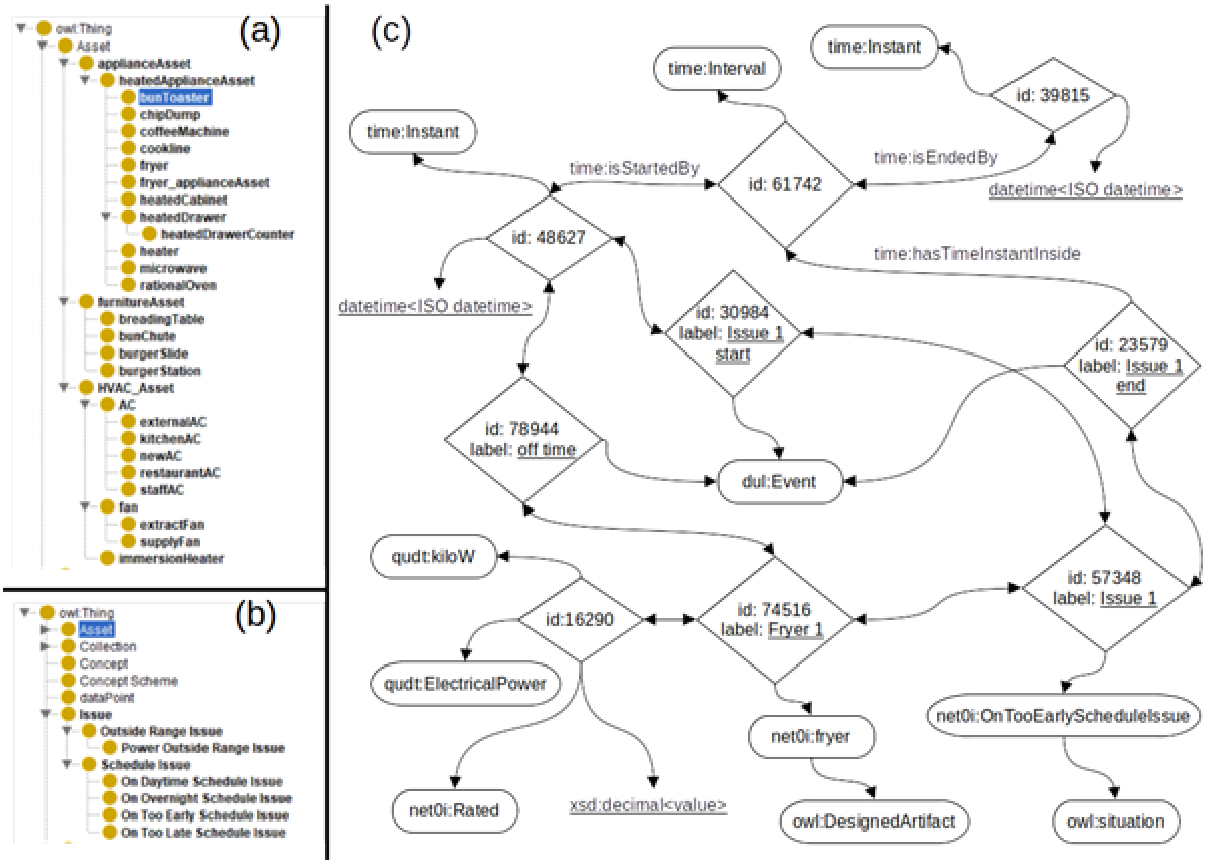

FIGURE 2. Parts (a) & (b) show classes used for representing equipment and issues in an ontology designed for QSRs. The schematic in Part (c) shows an example event where Diamonds are instances, Ovals are classes, Literals are underlined and Relationships shown by arrows.

tered the importance of a wide range of non-energy data to help put anomalies and patterns of energy use in the context of the organisational and business processes. This context is seen as the 'magic bullet' by facility managers to explain the reasoning behind anomalies; business context is necessary to fully understand changes in use. Such information is also key to ensure we can attribute the success of energy efficiency savings and research experiments and judge its overall effectiveness. However, context means different things to different stakeholders. This is why our categorisation of data types is not just a benefit for energy management, but almost a necessity to fully unravel the complexity and prevent misunderstandings when aiming for energy savings. This links to previous findings by Cuenca et al.[15] who call for a "common vocabulary" in their `DABGEO` ontology for energy management.

Another benefit of clarifying the meaning behind and listing the definitions of various forms of data types, thereby demystifying context, is that it paves way to arrive at a better organisation for knowledge repositories. A lot of the expertise in energy management relies on tacit knowledge, i.e., unstructured, loosely documented pieces of information, as well as information of low data maturity or hidden in various places such as embedded in policy reports or meeting minutes. Our ontological approach allows for capturing, linking, and re-using this information to be able to utilise context more meaningfully. This can enable pervasive researchers not only to gain clarity in their own work and presentation, but also improve communication to business stakeholders.

Ontologies as a Tool for Contextualising Energy Data

Many researchers in pervasive computing work with large quantities of qualitative data, such as interviews, desk research, conversational analysis, or focus group transcripts. While there are various techniques to analyse this data, such as thematic analysis, axial coding, or affinity diagrams, there is a barrier between time-series data and the rich context that qualitative data brings. We are often left to manually annotate figures with qualitative insights. Ontologies could provide a meaningful way to link the raw time-series data to the results and create cross-references to other data types such as quantitative data points, visualisations, recordings, or raw text files. This enables new synergies and opportunities for collaboration between qualitative and quantitative researchers, and provide a space for mixed-methods analysis. For example, in our research we collected rich information pertaining to the campus' energy management, ranging from focus groups with facility management, emails with administrators, and notes from conversations in liminal spaces.

We are interested in building a more rich picture of business systems beyond key performance indicators commonly used in energy dashboards. In so doing, we recognise how encoding context can perhaps unintentionally capture immutable snapshots of that emerges from dynamic activity.[13] Current dashboards are a blunt tool that communicate KPIs for energy and building performance, decoupled from lived experiences of occupants, business systems and policies. Our ontological approach is about codifying and bringing elements and dynamics of business systems and the use of energy systems into the decision making processes of stakeholders responsible for energy policy. Our approach is focused on contextualising energy decisions in a way that augments existing data-driven decision making with a mixture of signals from the lived experiences of building users, the business policies, and showing human impacts of energy policies or interventions. The focus of our approach is about surfacing and augmenting signals, experiences, and other data relevant to business systems that is easy to ignore when making decisions through the myopic lens of energy dashboards that focus solely on energy demand over time. We see this type of contextualisation of energy use in business and organisational terms as a necessary precursor to designing better tools for reflection and sense making with energy data.[16]

The ontological approach provided us with a better way to document and discuss these data and the results of its analysis. For researchers in pervasive sustainability this means it can not only improve the understanding of the results of data analysis internally, but also lead to a more holistic understanding of the causes for identified patterns and anomalies. While energy data visualisations have been subject of investigation in HCI for a long time, and the importance of capturing contextual data has been previously acknowledged[17] our approach goes one step further. We utilise the links unraveled by the ontological approach and the documentation of relationships between data and stakeholders to reflect on existing and influence future policies, which recent research argues is the most promising way to affect real change for a more sustainable future.[7]

Discovering Anomalies to Probe for Context

As highlighted by previous research, harnessing contextual data can be key to understand energy data and lead to more sustainable practices.[18] Ontologies have previously been suggested to allow semi-automated rule-based assessments of energy data, systematically identifying patterns and anomalies at an increased scale or more rapidity.[12] Due to our interdisciplinary research team of qualitative HCI researchers as well as experts in statistical analysis, we used this to our benefit by linking the emergence of anomalies (the *what*) with the reasoning based on qualitative data insights (the *why*). This offers a unique way to synergise time series data with interview data and strengthens the collaborative potential of work in our field. In our case study we used this to cross-reference operating hours with equipment use to identify energy savings potential, and the ontology allows us to directly store the results with explanations arising from the discussions that follow.

We have also analysed the campus energy consumption during COVID.[19] The ontological approach proved to be the most effective way to link statistical insights with the various pieces of information we captured to explain our findings. This proved useful not only for our own research methodology and documentation, but allowed for an improved communication with stakeholders when discussing our results and taking steps to generalise this type of research inquiry. While COVID was hopefully a singular occurrence, the lessons learned from this research can be invaluable to future policy implementations, as we considered the COVID lockdown as an extreme policy intervention.

The Inevitable Caveats

Our ontological approach provides several benefits, but as with almost any application, it does not come without limitations. Creating an ontology, or adapting an existing ontology to one's needs as is most common practice, takes time, effort, and knowledge. This is a challenge in organisations as it may cross cut roles, responsibilities and budget lines. We believe it is time well spent though, and the growing number of existing ontologies (e.g., `BrickSchema`[5], `QUDT`[6], or `DOLCE+Ultralite DNS`[7] just to name but a few) provide a good starting point. Ontologies also suit themselves better to trial and error; while setting up an ontology and filling it with data initially might take a bit more time than creating a time series or relational database which embed structural decisions, its structure is more malleable as it is not as rigid and can be altered later at any time without losing or corrupting existing data within in (within limits).

We also want to emphasise that we do not consider ontologies to be 'the solution'. Ontologies, in our view, cannot replace other tools such as conventional databases, digital twins, or data exploration dashboards, but they offer an important addition to create a blended environment in which several tools together form a strong framework. And just as established tools require training, experience, and maintenance to function well in a real-world setting, there is a similar need to embed ontologies in a useful and generalisable way into the research and practice landscapes to serve as tools for reflection.[20] In our project, the varying degrees of experience and expertise of researchers resulted in tools being developed to allow for a more versatile access. As is commonplace for new technologies introduced into a domain, there is a need for bespoke solutions until off-the-shelf solutions become widely available for quick adoption.

CONCLUSION

In this article, we analyse the various types of information that can be found in energy management settings, based on our past and ongoing work in the area. We present a novel approach, utilising a combination of ontologies to combine quantitative and qualitative data for providing energy management solutions that go beyond existing tools with just a narrow energy data focus. We believe the lessons learned from our research projects, in particular the documentation of the different data types derived from energy management discussions and analyses, illustrate the usefulness of ontologies in meaningfully analysing time series energy data and putting this into organisational context.

We believe such an approach can have significant value to organisations in capturing valuable context to help deliver more reliable insights for understanding and reducing the energy burden relating to their infrastructure and how it is currently used. We also hope tools built on this approach could help researchers and practitioners make better sense of the complexity of their data, enabling them to more accurately track the effectiveness of energy savings interventions, policy changes and research experiments. Such understanding is surely critical not just in the usual and sometimes rhetorical search to find energy savings and 'find efficiencies'; but rather, could help unpack and understand how energy gets embedded in emergent practice and infrastructures. Importantly, this should help us ask the harder questions about our often unquestioned presumption as to whether current levels of energy demand can and should continue, and where and how it can be reduced and reshaped.

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