A Multidimensional Model for Building Energy Management

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ABSTRACT

Data organization is a critical aspect in Building Energy Data Management. Yet, despite the importance of the topic, no sound reference model for energy data has been proposed in the literature. This work proposes a reference data model developed according to standard multidimensional modelling methodologies and improved iteratively in review meetings with users (knowledgeable in the energy management domain). The quality of the model is evaluated according to complexity, usability, and design metrics. Moreover, a BEMS prototype is built upon our model proposal, and validated with experienced energy managers. The end-result is a high-quality re-usable multidimensional data model that can be applied to create or improve on the data model designs of building energy management systems.

1. INTRODUCTION

To find energy-saving opportunities, energy consumption data must be analysed in the light of the factors that influence it. In buildings, this means analysing energy consumption in terms of multiple dimensions such as the arrangement of spaces, the specificities of constructive elements, the characteristics of the installed/commissioned equipment, and, ultimately, the behaviour of the occupants [1, 2, 3, 4, 5].

Decision Support Systems (DSSs) are well-known in management for supporting this sort of multidimensional analyses [6]. They enable managers to analyse vast amounts of data, identifying relevant knowledge, and choosing among different courses of action [7].

In this repository, data is (DW) [8]. In this repository, data is organized under a global unified schema that facilitates data analysis and presentation [9]. This reference schema, commonly known as a *multidimensional* model [10], is encoded using the core concepts of fact and dimension tables. Facts are observations regarding the business performance, and dimensions are the set of attributes that describe the business measurements [10]. Using a multidimensional model, distinct tools are able to cooperate, enabling managers to integrate, analyse and visualize large volumes of data—a degree of separation of concerns that largely explains the success of DSSs.

Building Energy Management Systems (BEMSs) are the decision support systems that support the energy management processes, that consist of monitoring, analysing, controlling, and optimizing energy usage. Overall, BEMSs minimize energy consumption, and maximize productive conditions and energy efficiency [11].

BEMS comprise activities such as *(i)* consolidating energy-related data from different sources, *(ii)* using data access tools to analyse building performance, *(iii)* visualizing energy-related data, and *(iv)* generating reports [12, 13]. All these activities must access a common data model.

Although the creation of multidimensional models is by now well established in the information systems domain [9, 10], creating a reference multidimensional model for energy management is hard. The explanation for this fact lies in the difficulty to obtain precise detailed requirements regarding energy management activities. First, existing energy management standards such as I. S. 393:2005 [14], ANSI/MSE 200:2008 [15], BS EN ISO 16001:2009 [16], and BS EN ISO 50001:2011 [17] do not agree on precise business requirements for energy management. Second, these standards do not deliver appropriate detail to enable deriving accurate information requirements [18]. In addition, it is well known that business process systematization is essential to obtain an accurate model formulation, without which many formulations are possible, but are either incomplete or inaccurate, thus resulting in increased development and maintenance costs [19].

The lack of a reference information model can be grasped in BEMSs with confusing user interfaces (that force users to throw away large amounts of data [20, 21]), and that are limited in terms of analysis capabilities (often forcing energy managers to use spreadsheets to analyse energy data) [22].

Regrettably, despite a few sparse contributions [13, 23], no proposal of a reference multidimensional model has been documented in literature that supports a broad range of activities underlying building energy management. This work develops and validates the design of a multidimensional model for building energy management that seamlessly supports a broad range of energy-related data analysis activities. Our model proposal is grounded on well-established principles of multidimensional modelling and patterns developed by Kimball et al., thus achieving a high quality model that is simple to use and modify [24].

To complete our work, we validate our model according to multidimensional model quality metrics, including complexity, usability, and design quality metrics. In addition, we develop a BEMS prototype to validate the model with energy managers.

In the following section we analyse the requirements of data warehousing and multidimensional models for energy management decision support. Section 3 describes our multidimensional model solution. The model is then evaluated according to distinct metrics of complexity, usability, and design quality (Section 4.1). Section 5 describes the BEMS

prototype solution and evaluation. Existing multidimensional model proposals from the literature are discussed in Section 6. Section 7 presents the conclusions and implications of our work.

2. ENERGY MANAGEMENT DECISION SUPPORT

Building Energy Management Systems can be understood as decision support systems that support energy management processes: they monitor, analyse, control, and optimize energy usage. Indeed, similarly to DSSs, BEMSs collect and store building energy consumption data from meters, sensors, and other sources, enabling managers to analyse how energy is spent. Data is then consolidated to enable identifying energy-saving opportunities, forecasting energy consumption demand, detecting anomalous situations, performing improvement actions, and measuring energy saving strategies outcomes [11, 25].

There is no consensus in the literature regarding what is the appropriate architecture for a BEMS. Existing proposals fit into a generic architecture consisting of a building automation layer, a data management layer, a performance optimization layer, and an application layer [13, 23, 26, 27, 28]:

Building automation layer contains building automation systems, such as meters and sensors, and provides data types such temperature and luminance that are related with building performance.

Data management layer collects and stores data from the building automation layer into a data storage system, such as a DW.

Performance optimization layer evaluates energy performance, optimizes the equipment functioning, and warns users about abnormal situations.

Application layer provides a user interface along with a set of tools, which are used by the users to parametrize the system, analyse data, obtain reports, and control equipment functioning. Some examples of tools are OLAP (Online analytical processing) tools.

2.1 DW for Energy Management

The DW preserves history, storing activities and events occurred over time. Also, it is optimized for accesses involving a huge number of records, quickly responding to complex queries over stored data. Moreover, the DW extracts, transforms, and stores data from multiple heterogeneous sources, assuring data quality and consistency [8, 9].

A DW can be understood as a system comprising operational data source systems, a data staging area, a data presentation area, and data access tools [29].

The operational source systems provide input data. Usually, they support different business areas, and use disparate technologies and formats for staging data [29]. In building energy management context, the operational source systems correspond to the building automation layer of the BEMS.

In order to take advantage of data sources, data is extracted and temporarily persisted in the data staging area (DSA). Extracted data is integrated, modified to solve data quality issues, and delivered into the presentation area. That process is known as ETL (Extract, Transform, Load) [30].

In the presentation area, data is organized and stored under a global schema (multidimensional model), to be analysed and queried using data access tools (e.g. OLAP tools) [29, 31]. On BEMS, the data management layer is represented by the DW presentation area.

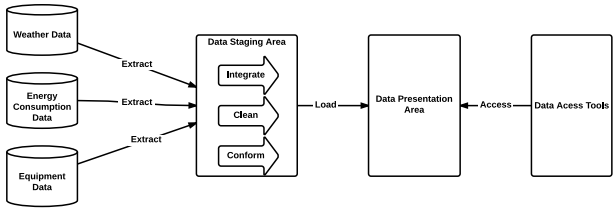

Figure 1: The main components of a DW: represented from left to right. Operational Source Systems, Data Staging Area, Data Presentation Area and Data Access Tools. The ETL activities are also represented: extract, transform (integrate, clean conform) and load. Adapted from [10].

The data access tools support activities that explore data from the data presentation area, and are part of BEMS application layer. Data access tools are responsible for delivering consumable information to the end-user [29]. The overall DW architecture is depicted in Figure 1.

2.2 Multidimensional Model

Multidimensional models are used for storing data in the data presentation area that besides efficiency, ensures a number of other aspects [32]. Models provide developers with an abstraction of data, enabling them to explore different design solutions, associated risks, and resulting costs, without getting lost on the details of a system that might be large and complex. Moreover, the model captures well the user requirements and domain knowledge, and therefore, developers and stakeholders may use it to communicate and agree on them [19, 32, 33, 34]. These reasons make the multidimensional model a central point of a DW.

In the context of building energy management, the multidimensional model aggregates data associated with factors that impact energy consumption. For instance, energy measurements data is stored in a fact table, which is described by space data (on space dimension), equipment data (on equipment dimension), and time and date data (on time and date dimensions).

3. MULTIDIMENSIONAL MODEL DEVELOPMENT

In literature, there are two major DW development methodologies. The methodology created by Inmon follows a top-down approach, which relies on IT professionals depth knowledge of business processes and their previous definition [9].

The methodology developed by Kimball et al. (known as the Kimball lifecycle) follows a bottom-up approach [24]. In concrete, Kimball's methodology consists of defining the business processes model targets; determining data granularity, and model dimensions and facts. Unlike the top-down approach related concepts, bottom-up concepts, such as facts and dimensions, are easier to understand by end-users, easing their collaboration on the development process. This aspect is particularly important on the building energy management context, where users intervention compensates for the lack of business processes systematization. For these reasons, we follow the Kimball lifecycle methodology to develop our multidimensional model [9, 24, 35].

In order to perform the previous steps, in the context of BEMS, it is necessary to consider *(ii)* the underlying data sources *(i)*, and building energy management processes [10]. The following sections describe the data sources and business processes related to building energy management.

3.1 Energy Related Data Sources

The identification of the major data sources was based on the review of energy management standards, and energy data analysis activities. In addition, we enquired several energy management domain experts about the relationships between distinct data types. Accordingly, the major data sources that have to be integrated into a multidimensional model for building energy management are the following:

Energy Metering Data refers to energy consumption data, and quantifies the energy required to perform business activities on a given space area (optionally using an equipment), at a specific time interval [25, 36, 37].

Energy readings are also associated to a *datapoint*, which aggregates the properties that describe an energy measurement (e.g. precision, and scale).

Building Spaces Data is concerned with capturing the organization of the building envelope. Each space entity can be an atomic space or an aggregation [38].

Equipment Data encompasses devices that consume energy in the context of business activities, and are located in a building space.

Building Space Occupancy Data influence energy consumption depending on the number of occupants, their activities, and their behaviour [1, 4, 39]. In buildings, energy consumption varies with occupancy.

Organizational data is used by BEMSs to allocate costs per organization or individual members. It captures the structure of organization elements, i.e., groups of one or more people business realizing activities [40, 41].

Weather data is related to the environmental conditions (e.g. temperature, wind speed, and solar radiation) of a specific location. This information is important since there is a relation with energy consumption in buildings [2, 5, 25, 42].

Energy costs usually vary on fixed time schedules (e.g hourly, and daily). The cost has a fixed component, and a variable component that depends on the current energy demand, the estimated energy consumption, among other factors [43, 44].

Step	Output
1. Identify the business processes	**Business processes** • Analysis of buildings energy consumption, • Analysis of weather conditions impact on energy consumption, • Analysis of energy costs evolution over time, • Analysis of space occupancy and activities impact over energy consumption.
2. Declare the grain	**Measurements and their granularity** • Energy consumption readings (every 15 minutes), • Weather readings obtained (every 30 minutes), • Space occupation (every 30 minutes), • Energy Costs information (every month).
3. Identify dimensions	**Dimensions and their associated roles** Time and Date (when), Space (where), Organization (who), Equipment (how), Activity (what), Datapoint.
4. Identify the facts	**Facts and their associated fact tables** • Energy measurements (energy readings fact table), • Weather readings (weather readings fact table), • Heating and cooling degree days (degree days fact table), • Energy costs and tariffs (energy costs fact table), • Measured occupation (occupancy fact table).

Table 1: Output of the four-step design process of the Modelling phase, from Kimball Lifecycle, and instantiated to the Energy Management domain.

3.2 Building Energy Management Processes

The identification of business processes is a fundamental step to limit the number of design targets and correctly define the grain, dimensions, and facts [10]. To identify building energy management business processes, we reviewed energy management standards [14, 15, 16, 17, 45]. However, the standard's description of energy management activities is not backed by concrete requirements nor described with sufficient detail [18], hampering the identification of business processes the multidimensional model must support.

An alternative way of determining the business processes is considering the energy consumption analysis methods and techniques reported on the literature as described in literature, and then inferring the underlying business processes. In particular, studying the impact of weather conditions on energy consumption [2, 5, 39, 42, 46, 47, 48, 49], analysing the impact of space occupancy and occupant behaviour on consumption [4, 46, 50, 51, 52, 53], and evaluating the evolution of energy costs and tariffs over time [43, 44, 54, 55]. In addition, we considered the process of analysing energy consumption in buildings [14, 16, 17, 18, 44, 56, 57].

Taking into account the identified data sources and business processes, we were able to complete the analysis steps of declaring the grain, identifying the dimensions, and identifying the facts [10, 24]. The details are presented in Table 1. Using these analysis steps it is then possible to inform the model design, as described on the following section.

3.3 Multidimensional model solution

During the execution of building energy management business processes, energy consumption related metrics are recorded and stored as fact table measurements. Thus, the core of the multidimensional model consists of four fact tables: **energy measurements**, **weather readings**, **building space occupancy**, and **energy costs**.

The major dimension tables are **time**, **date**, **space**, **equipment**, and **datapoint** dimension. Additionally, the model contains other constructs, such as hierarchy bridges and group bridges, resulting from the application of multidimensional design patterns. The complete model representation is given on Figure 2 using the crow's feet notation [58].

The application of multidimensional modelling design patterns depends on the problem specificity and context. We now describe design choice and modelled situations.

3.3.1 Fact table design choices

An important decision for storing energy data is deciding what type of fact table to use. Transaction fact tables represent events (e.g. energy or weather reading) related to moments in time, which are stored in single rows [10]. On the other hand, snapshot fact tables take a "picture" of

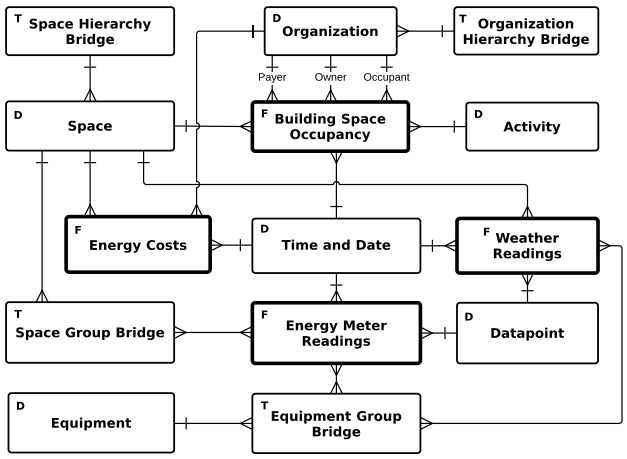

Figure 2: Representation of the complete multidimensional model. In order to increase legibility, we merged Time and Date Dimension rectangles into one, and weather readings fact and degree days fact table rectangles into one. The rectangles left upper corner's F stands for fact, D stands for dimension, and T stands for table.

all the events occurred in a period frame without worrying about single events [10].

Considering its characteristics, transaction fact tables are the most appropriate choice to represent single energy measurements, energy tariffs, single weather readings, and space occupancy recordings.

3.3.2 Multiple transaction fact tables

Using multiple transaction fact tables allows more descriptive dimension attribute names, instead of a single fact table with generalized names that compromise the model understandability.

An important design decision is deciding if energy consumption and weather data should be stored in a single fact table or in multiple fact tables. Despite being correlated, energy consumption measurements and weather readings are analysed differently, and data comes from different sources [5]. Taking into account these differences, creating distinct fact tables is the most sensible solution [29].

3.3.3 Multi-valued dimensions

In the multidimensional data model, dimension table rows are related to the fact table by a one-to-many relationship [59]. For instance, the same dimension row may be associated to many energy measurements (the measurements that took place on that given day). However, sometimes it is difficult to model data according to this one-to-many relationship pattern. Suppose, for example, that an energy measurement is done by multi-sensor equipment installed in different building spaces. In this case we have two many-to-many relation:

- Many-to-Many relationship between energy measurements and equipment
  1. Each energy measurement is recorded by several equipment sensors working together.
  2. Each equipment records many energy measurements.
- Many-to-Many relationship between energy measurements and building spaces
  1. Each Energy measurement is associated with the different spaces where the consumption occurred.
  2. Each Space is associated with several energy consumption recordings.

This issue is known as the multi-valued dimension problem [31]. One of the best solutions to overcome this problem consists in using an intermediate table to serve as a bridge between the fact and dimension tables [59]. Essentially, the fact table is connected by a many-to-many relationship to a group bridge table, which contains an individual row for each element in a group. For instance, an energy measurement associated with three spaces is assigned one group with three space rows [10]. In order to solve multi-valued dimension issues, our model includes space and equipment bridge tables.

3.3.4 Role-playing dimensions

A role-playing dimension is referenced by two or more fact table foreign keys. Each key represents a role, which is described by a name, and is associated with a dimension table view [29]. Analogously to bridge tables, role-playing dimensions are used to model many-to-many relationships. However, they require a fixed relationship cardinality—a fixed number of roles [30].

One interesting instance of application for role-playing dimensions is when modelling occupancy. Occupancy may be associated to three organizations that may be different: the one who pays for the space, the one who owns it, and the one who is occupying the space. Accordingly, we use a role-playing dimension to model this.

3.3.5 Variable depth hierarchies and hierarchy bridges

A hierarchy bridge table has an entry for each relationship between an entity and its parent, enabling to navigate through the hierarchy. Hierarchy bridge tables are placed between a fact and a dimension table, and do not require neither of them to be modified.

A model for building energy management must handle hierarchies with variable depth, namely *(i)* the organization hierarchy, and *(ii)* the building space hierarchy. Both cases require using a hierarchy bridge table to model their hierarchies.

4. VALIDATION

A reference multidimensional model for building energy management must be evaluated. However, To the best of our knowledge there are no literature proposals regarding the validation of multidimensional models quality evaluation. Accordingly, we developed a model validation methodology, in which the model is validated using metrics proposed on the literature, performing workload tests as described by Golfarelli and Rizzi, and reviewed by end-users [60]. All evaluation steps were part of an iterative process, and in which model anomalies are corrected and improvements. The precise evaluation metrics and workload tests will be detailed along the coming Sections.

4.1 Multidimensional Model Validation Context

The quality of the multidimensional model must be assured at distinct phases of DW development cycle. During the modelling phase, the model is validated with business users to confirm the accuracy of data requirements. Whenever users do not understand the model, they have to rely on the interpretation conveyed by developers who may have misinterpreted the original requirements [32]. Multidimensional models are usually the first artefacts to be tested since their early validation is fundamental to find errors, much like any other software engineering artefact [60, 61]. For instance, assessing the model quality before designing ETL processes reduces the impact of design errors [60]. Overall, the quality of the multidimensional model translates into the cost and time required to develop the DW, which in our case is embodied in the BEMS.

The multidimensional model evaluation procedure was applied iteratively until there were no significant changes on the schema. Changes arose from improvements identified after workload tests, and evaluation with metrics or end-users.

The multidimensional model quality metrics employed are those proposed on the literature to measure different model qualities of structural complexity [62], cognitive complexity [63, 64], usability [60, 65], and design quality [10, 24].

4.1.1 Validation Methodology

The multidimensional model evaluation procedure was applied iteratively until there were no significant changes on the schema. Changes arose from improvements identified after workload tests, evaluation with metrics or end-user review sessions.

Model evaluation metric results were obtained using a model evaluation tool specifically developed for the purpose. Some metric results were calculated manually (e.g. number of snowflake constructs). In all cases, metric values were stored by the Java tool, enabling the comparison of the results obtained for different design alternatives.

End-user review sessions were executed with the participation of 8 users and lasted an average of 90 minutes each. Each session involved one or two users at a time, and consisted of *(i)* explaining the concepts and the latest modifications, *(ii)* discussing the designations used, *(iii)* asking them what denominations should be improved, and *(iv)* inquiring them about improvement suggestions.

The evaluation and improvement process lasted eight weeks. During the first five weeks, end-user review sessions were performed with five users, who have been taught how to interpret a multidimensional model. The participants had previous experience in building energy management domain.

Over the sixth week, the schema was not being significantly modified any more and we could not identify any significant improvements. The final end-user review sessions were performed with three experienced energy managers.

4.2 Metrics Evaluation Results

Overall, both workload tests and user reviews contributed to improve the model completeness and easiness of use. However, experience energy managers demonstrated difficulty in identifying model improvements, without having possibility of performing concrete energy related analyses. Therefore, reinforcing the need of performing user review sessions, in which we demonstrate the functionalities of a BEMS built upon our model.

During the model evaluation with metrics we could not take a conclusion about the model complexity, which is associated with its understandability and maintainability. Although, we confirmed a high level of model usability, and thus its high learnability, ease of use, and flexibility when performing energy-related analyses, and low performance impact on the underlying system. In addition, we demonstrated the model high design quality.

Despite the validation against a static model structure, the model may be simplified or extended. For instance, variable depth hierarchies may be replaced with fixed depth hierarchies. Indeed, the proposed model qualities along with the guarantees provided by the use of Kimball lifecycle [24] development guidelines, enables us to affirm that our model is easily modifiable.

5. BEMS PROTOTYPE SOLUTION

The lack of empirical testing is an obstacle to the effective evaluation of the quality of conceptual models [33]. As for multidimensional models, the lack of empirical testing limits the assessment of whether the model is fit for purpose, i.e., the model supports the required BEMS functionalities. Therefore, we validate our model by developing a BEMS prototype built upon our model proposal, using university campus building data (e.g. buildings, and energy data).

From a technical point of view, our solution consists of three independent modules: *(i)* the definition and execution of ETL processes to integrate data, *(ii)* the development of an OLAP web server serving energy data analysis requests, and *(iii)* the development of energy management web applications, enabling users to pose data analysis requests.

The prototype is validated conducting interviews with energy managers. The purpose of the interviews is to evaluate the usability, performance, and functionality of a BEMS built upon our model, resulting in an additional model validation.

5.1 BEMS Prototype Development Context

According to the distinct BEMS architecture components described in Section 2, our prototype will focus on the data management and application layers. Those are the BEMS layers required to evaluate our model. The development of building automation and performance optimization layers goes beyond the scope of this work.

Our BEMS prototype closely follows the architecture of a

Question ID	Description
Design	
Question 1	The application interface is pleasant to use
Easiness of Use	
Question 2	The application interface is easy to use
Learnability	
Question 3	It is easy to learn how to use the application
Question 4	The information provided by the application is easy to understand
Satisfaction	
Question 5	I am satisfied with the outcome of performed tasks
Performance	
Question 6	The user interface is highly responsive

Table 2: Description of usability questions posed during interviews with energy managers.

DW. In that architecture, our BEMS prototype includes the following components:

1. Data management layer consists of:
   (a) A DW data staging area loaded by ETL workflows that extract and conform energy-related data.
   (b) A DW data presentation area including a data storage and an OLAP web server.
2. Data application layer represented by data access tools in the form of energy management web applications.

In the following Sections we describe the major solution components, namely ETL workflows, OLAP web server, and energy data analysis applications.

5.2 ETL Workflows Development

A DW system relies on a unique data storage containing clean and cohesive data, that enable users to perform business related analysis [30]. The effective design and implementation of the appropriate ETL workflows are a significant part of the DW development process.

Our choice for implementing ETL workflows was Pentaho Data Integration Software (PDI). PDI is a professional grade open-source ETL tool, that enables the definition and execution of ETL processes, and is supported by a growing community. We used PDI to extract data from sources, transform data according to the model specification, and load data on a data storage (PostgreSQL relational database).

5.3 OLAP Web Server

Despite their advantages, MOLAP systems rely on proprietary OLAP databases [24]. Therefore, our solution was developed according to a ROLAP architecture. Our system architecture relies on a PostgresSQL relational database, a XML metadata repository, an OLAP web server, and web data analysis tools.

Our web server relies on Pentaho Mondrian OLAP engine, which we will simply call Mondrian. Mondrian is a Java library that receives MDX query requests, generates optimized SQL queries, and executes them over a relational database. For that purpose, the multidimensional model was loaded as a relational database model on PostgreSQL relational database.

The OLAP web server query requests are received through a REST API, represented by a single URI (/Application), that has a GET method with parameters for MDX query clauses described as follows:

The *cube* MDX query clause contains the OLAP cube identifier, from which data is to be retrieved; *rows* clause determines the OLAP cube rows data; *columns* clause defines the OLAP cube columns data; *with* clause is the MDX query clause that specifies an expression to be applied over a set of tuples within the cube; and *where* clause contains an expression that determines the dimension hierarchy used to slice the cube, obtaining a one-dimension cube slice [66].

The translation between MDX and SQL queries is defined on Mondrian metadata repository using XML files conforming to Mondrian XML schema. Our Mondrian XML metadata file contains the following definitions:

Physical Tables Metadata includes relational database table attributes and their corresponding data types.

Dimensions Metadata is used to map relational database tables with multidimensional model dimensions, determining dimension attributes, setting attribute dependencies (e.g. each month belongs to a single year), and defining dimension hierarchies.

Cubes Metadata determines OLAP cube dimensions and measures.

5.4 Energy Management Web Applications

In order to develop energy management analysis applications, we developed interactive web chart applications for energy management, according to the reporting techniques and analysis methods described on literature [44, 67, 68].

Our web charts application follow a common execution procedure, in which they read chart configuration parameters, build MDX query clauses, send query requests to OLAP web server, parse the response data, and build charts according to the requested configurations. Those steps are described as follows:

1. Users start by choosing one of the available charts, depending on their data analysis goals. For instance, the detailed analysis charts enables users to inspect a single building hourly energy consumption.
2. After choosing the most appropriate chart, users configure the chart. The major chart configuration parameters are the selection of one or more buildings, the selection of a normalization criterion (e.g. MWh, MWh/m^2, and CO_2 Kg), and the selection of a time granularity (e.g. yearly, monthly, and weekly).
3. According to the chosen chart parameters, the chart application requests its specific query builder to determine the MDX query clauses (e.g. rows, columns, and cube) required to create a chart that displays data according to user request.
4. The set of constructed query parameters is sent to the OLAP Web server, that verifies the received MDX query clauses validity, builds a complete MDX query, requests mondrian to execute the MDX query over the postgres data storage, and answers back with a JSON matrix array containing query results data.
5. The chart application parses the data matrix array according to the expected query result structure.
6. After parsing the matrix array data, the web chart data is updated according to the requested chart configurations.

On the following paragraphs we describe the major aspects of each chart type.

5.4.1 Detailed Consumption Analysis Chart

Detailed Analysis bar chart enables users to inspect energy consumption trends in different time periods, going from years to minutes.

5.4.2 Space Comparison Analysis Chart

The goal of space comparison bar chart is comparing buildings consumption performance, over a time period. For instance, it is possible to compare the consumption of North and South Tower, during the fifty-two weeks of 2014.

5.4.3 Year Comparison Analysis Chart

Year Comparison chart is similar to space comparison chart, but instead of being used to compare consumption

on different spaces (on the same year), it is used to compare consumption on different years (on the same building). Moreover, it presents a ratio curve that represents consumption evolution ratio over the years.

5.4.4 Consumption Variables Analysis Chart

Energy consumption is influenced by different factors, such as temperature or humidity. In order to enable users to study variables influence on energy consumption, we developed a scatter chart, which includes a regression curve. The X axis has the weather measurements scale (e.g. degrees Celsius), and the Y axis contains the energy measurements scale (e.g. MWh).

5.4.5 A4 Room Occupation & Activities Analysis

Two factors that highly influence energy consumption are space activities and occupants behaviour. While performing activities, users rely on heating or cooling air systems, illumination systems, and other various equipment. Therefore, we developed a chart to represent the correlation between energy consumption, academic lessons, and students occupation, on Taguspark A4 lecture room.

5.4.6 Energy Costs Simulator

Energy manager's major goal is reducing energy costs. Likewise, BEMSs must enable managers to analyse energy costs, so they can evaluate energy management policy effectiveness results, compare different supplier costs, and analyse the impact of tariff or fixed energy cost changes on the total energy cost.

5.4.7 Peak Load Analysis Chart

Peak load analysis is used to identify high energy demand periods and configure equipment functioning accordingly. On the other hand, base load is associated with constant energy consumption; some equipment function uninterruptedly throughout time, resulting in permanent minimum energy consumption values.

5.5 Evaluating the BEMS Prototype

The BEMS prototype evaluation consisted on interviewing experienced energy managers, who are responsible for buildings with considerable energy consumption (e.g. office buildings). The aim of the interviews was the evaluation of BEMS prototype front-end, which users interact with, obtaining a perception of the overall system functionality and quality [60]. Also, front-end evaluation results may depend on the prototype performance and usability issues. Likewise, the interview questionnaire was split in two parts: one for evaluating the prototype usability and performance, and another to evaluate energy consumption analysis methods.

Usability evaluation questions were based on the ISO 9241, standard for ergonomics of human-computer interaction [69]. The questions aim at evaluating the BEMS interface design, easiness of use, learnability, and satisfaction.

Performance evaluation was associated with a question, in which we asked the users to classify the prototype performance and responsiveness from one (slow and unresponsive) to five (fast and responsive). In addition, we recorded BEMS user interface response time during interview sections.

Functionality evaluation consisted of *(i)* identifying energy consumption analysis methods missing on the prototype, and *(ii)* identifying necessary improvements on the provided analysis charts – missing data filters, or other features necessary for an effective consumption analysis.

5.6 BEMS Prototype Evaluation Methodology

During the evaluation of the BEMS prototype, we performed 11 interviews with experienced energy managers, responsible for different types of buildings, used for different purposes (e.g. education, culture activities).

Interviews were performed on the energy manager's office, and took an average of 90 minutes each. The interviews were semi-structured, allowing energy managers to interrupt any time, and having us determining the interview course along the way. For instance, during some interviews we were able to see the organization BEMS functioning, or hear about implemented energy policies. Nonetheless, we always obtained answers for all the questions.

The interview structure consisted on the following:

1. Explaining to the participants the work context (e.g. BEMS prototype purpose and objectives), and the multidimensional model entities and relationships.
2. Performing a demo of each energy consumption analysis chart, and giving hints about energy consumption analysis results obtainable using those charts.
3. Requesting energy managers to verbally answer our questionnaire.
4. Asking energy managers to provide feedback, comments, and suggestions about the prototype, or any clarification about their work specifics (e.g. energy management analysis methodologies) or any other aspect, such as building characteristics, or implemented energy reduction policies.

5.7 BEMS Prototype Evaluation Results

Overall, BEMS prototype evaluation demonstrates that our multidimensional model supports a broad range of energy data analysis methods, and does not comprise the underlying system performance, thus demonstrating the applicability of the model in real-world settings.

Regarding the usability evaluation results, the prototype must be modified to provide more context information to users, and supply less restrictive data filter tools. In either case, the lack of such improvements did not comprise usability evaluation results.

After applying minor modifications on the model, our model supports the analysis of gas consumption, energy cost simulations, and the correlation of events with energy consumption. In general, the functional evaluation results demonstrate that our model is highly extensible.

6. RELATED WORK

The number of literature references that propose multidimensional models for energy management is small. Another striking aspect is that, the quality of existing models was never evaluated. Despite being well established that model quality influences several parts of DW development cycle (e.g. stakeholders communication and requirements validation), and constrains the overall DW performance [32].

A fundamental aspect of a multidimensional model is the flexibility of the model with respect to the dimensions that influence energy consumption. A more flexible model enables managers to analyse a larger spectrum of energy consumption factors [70].

Different authors agree on the existence of a primary set of dimensions, such as *(i)* a time dimension, *(ii)* a location dimension that captures building locations, *(iii)* a measurement/sensing device dimension, and *(iv)* an organization dimension that aggregates data from individual occupants to the organization level [13, 23]. However, existing models typically lack dimensions such as energy costs and user occupancy as proposed in other models (e.g. [71])—that our proposal also supports.

Some models are acceptable in terms of flexibility but present design issues. Li et al. presents a model that is relatively complete but includes a dimension called external that stores all energy consumption related measurements [71]. Those measurements cannot be stored as dimension attributes, which are used to describe energy measurements context (e.g. related space, equipment, organization). Thus, each energy consumption related measurement category should be stored in at least one fact table [10].

Li et al. model also includes a renewable energy dimension requiring all energy consumption measurements to be associated with a renewable energy dimension entry, which may not always happen. Therefore, the model should include a degenerate dimension to distinguish renewable and non renewable energy sources, or a junk dimension identifying the source type [10].

Another modelling issue is modelling of fact tables as dimension tables. This problem is found in modelling of energy tariffs, that should be modelled as facts because they vary over time and according to supplier, location, and organization unit. In addition, they are associated with the process of analysing energy costs, and should be stored in a fact table [10].

Another problem is including dimensions in the model that are too specific. The model proposed by Gökçe and Gökçe includes an HVAC dimension instead of an equipment dimension. Likewise, the remaining types of equipment (e.g. illumination) will be stored in new individual dimensions, resulting in the creation of a centipede fact table—a fact table with too many dimensions. Such fact tables are known to compromise queries performance, and ultimately, the system usability [10].

The multidimensional model proposed by Hong-ye et al. includes separate dimensions for date and time [72]. This aspect is important in building energy management context, where managers analyse data summarized by years, minutes, or seconds [44]. Furthermore, having separate time and date dimensions reduces date dimension number of rows, that would otherwise end-up storing millions of rows, compromising the underlying system performance [10]. Despite the importance of having both time and date dimensions, other authors include solely a date dimension on their models.

Overall, and to the best of our knowledge no model has been proposed in literature that is as comprehensive as ours, or that addresses multidimensional design anomalies in a such systematic way as we propose. Moreover, none of the proposed designs undergoes any rigorous validation according to design metrics.

7. CONCLUSIONS

Energy consumption analysis is performed by energy managers using BEMSs, which can be regarded as DSSs instantiated to the energy management domain. Despite DSS development being already well established in the Information Systems domain, BEMS still lack a reference information model that can be re-used to integrate energy-related data from heterogeneous data sources, and facilitate the integration of data analysis tools, alleviating the overall effort required for systems development and maintenance.

The difficulty to obtain precise requirements regarding energy management business turns the creation of a multidimensional model for energy management into a challenging task. Indeed, no multidimensional model proposals in the literature support a broad a range of building energy management data analysis activities. As we demonstrate in our related-work analysis, existing models present several multidimensional modelling design issues, and to the best of our knowledge none was validated.

In contrast to other proposals, our model was designed according to widely accepted multidimensional modelling principles and DW development guidelines, namely role-playing dimensions and hierarchy bridges. Our approach is innovative in that we followed the bottom-up DW development approach of Kimball et al. and leveraged end-user collaboration on validation of the multidimensional model development process, to overcome the lack of business process systematization [24].

Another merit of the model developed in this work lies in the iterative validation process employed, that consists of *(i)* the evaluation with multidimensional model design quality metrics proposed on literature, *(ii)* testing the model against a wide range of queries, and *(iii)* the model revision by users with building energy management domain knowledge. The outcome is a high quality model. In concrete, evaluation results indicate that our model is easy to use, flexible for users to perform energy-related analyses, has a low impact on the underlying system, and is easily extensible.

To further validate the model proposal, we developed and validated a BEMS prototype built upon our model. The prototype was validated during interviews with experienced energy managers, in which energy managers referred the variety of provided energy data analyses (supported by the model), and made several improvement suggestions. Due to the high model completeness, these suggestions only require the application of minor modifications on the model.

Our multidimensional model proposal documents how common multidimensional model design anomalies are addressed and constitutes a step towards the systematization of BEMS system requirements and energy management domain knowledge. Moreover, the existence of a reference multidimensional model design for building energy management contributes to a better integration between BEMS system components, and eases data analysis tools development, reducing BEMS development and maintenance costs.

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