Towards Automating the Deployment of Energy Saving Approaches in Buildings

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Abstract

Almost 32% of the total energy consumption in industrialized countries is used for electricity, heating, ventilation, and air-conditioning (HVAC) in buildings. Deploying Energy Management Systems (EMS) helps reducing energy use. Unfortunately it is a complex task that requires to identify the EMS inputs among thousands of sensors in a building. Since most of these sensors lack any labeling standard this is currently done manually. We aim to semi-automate this mapping task and address the problem of identifying EMS inputs with minimal user involvement. This is achieved by utilizing linguistic and semantic techniques for computing similarity values between labels of sensors and EMS inputs. Experiments show that our approach can be successfully applied to real-world data.

Categories and Subject Descriptors

I.2.1 [**Computing Methodologies**]: Artificial intelligence—*Applications and Expert Systems*; I.2.4 [**Computing Methodologies**]: Artificial intelligence—*Knowledge representation and reasoning*; I.2.6 [**Computing Methodologies**]: Artificial intelligence—*Knowledge acquisition*; H.4.4 [**Information systems**]: Applications—*Decision support systems*

General Terms

Algorithms, Measurement, Management

Keywords

Label Mapping, Linguistic Matching

1 Introduction

For large companies building energy management is done at enterprise scale that enables them to monitor, analyze, report and reduce energy consumption across their building portfolio, including retail and office properties. However, the integration of buildings in different locations, with different systems and technologies is a challenging task. Particularly, the large number of several thousand sensors renders it hard to identify the relevant data for energy management.

Energy management systems (EMS) usually reside on top of the individual Building Management System (BMS) that implements the building control. In order to identify the relevant data for energy management one needs to know how they are labelled in the BMS. Unfortunately, BMS are not systematically labeled. In contrast, technical systems in buildings are usually installed by specialist and the heating, ventilation, and air-conditioning (HVAC) systems are added by different parties than the lighting, shading, or energy system. This reflects on BMS level in a high diversity of labels as every integrator uses his own naming scheme to label data points. The situation gets worse every time a system is added or replaced by another person with his own way to label similar functionality. In result, each BMS has a unique labelling scheme that is often not even consistent in itself. Thus, deploying EMS can take several weeks of full-time work. In result, industry sees the labelling problem as a major stepping stone for novel analytic approaches in buildings [4, 10].

Standardization efforts try to approach the problem from different angles. Network protocol standards regulate the semantics in communication networks [9], but are not reflected on BMS level. Building Information Models [8] specify models for structural, mechanical, and electrical aspects, but not the data labels. Labelling recommendations such as Haystack [7] are under development, but are not established. Ontologies [11] provide homogeneous semantic models, but require mapping of BMS labels.

Schema matching is a similar problem in data bases, where data elements need to be mapped between two distinct data models. Due to the rich information available in database, the approaches can utilize different similarity measurements from linguistic matching of column names to the correlation of the data [2].

Semantic matching techniques [5, 14] use linguistic and structural similarity measurements to match semantic models. However, they require that the input is already in a semantic format and that structural knowledge is provided by a domain ontology. In our case we only consider large sets of textual labels and no other source for similarity.

We present a novel approach for semi-automating this mapping task. It uses semantic techniques for computing similarity values between BMS and EMS labels. Thus, the

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user has no longer to consider thousands of BMS labels for identifying the ones that need to be mapped to EMS labels but can instead be presented with a list of possible mappings that are sorted according to their similarity values.

To show the effectiveness of our approach in reducing the number of BMS labels that need to be manually considered by a user we have evaluated our method using real-world data from IBM's research living laboratory building in Dublin, Ireland.

The paper is organized as follows: The next section introduces a running example that is used throughout the paper. Our method for computing similarity values between BMS and EMS labels is presented in Section 3. The applicability of our approach is demonstrated for real world data set in Section 4. Section 5 concludes the paper with some remarks on future work.

2 Running Example

We demonstrate our approach for data from IBM's research living laboratory building in Dublin. Table 1 lists a small excerpt of the point list. The second column shows BMS labels for the return and supply air temperature of three different Air Handling Units (AHU) as well as an outside air temperature sensor. Different persons installed these three AHUs and each one used his own labelling scheme. The third column states what the integrator intended to encode in the acronyms. The last column is the semantic EMS label that we intend to extract with our approach.

The example illustrates some characteristics of BMS labels. Common for all BMS labels is the usage of acronyms combined by separators (underscores in this case). The acronyms are usually not random, but follow some personal labeling scheme specific to the involved system integrator. All BMS labels encode the asset and the semantic type. The simplest form of variability is the usage of different abbreviations for the same term. For example, `SAT`, `DAT` and `SUP_TEMP` all stand for the EMS type `supply air temperature`. `SAT` is an abbreviation of all three nouns. `DAT` replaces `supply` by `Discharge`. `SUP_TEMP` joins two abbreviations for `supply` and `temperature`, but, lacks `air`. Nevertheless, in all these cases a lexical similarity between labels and their meaning exists. Only in line L8 we have a BMS label containing `Ext` which stands for external, but has no lexical similarity with the label `Outdoor` defined in the EMS marker set.

3 Computing similarity values

We use an ontology to semantically define the EMS labels that we want to extract. Ontologies are an extensible knowledge model and provide semantic reasoning capabilities [1] that will help to solve our mapping problem. Relevant for our approach is that an ontology defines common *semantic concepts* and *individuals* of these concepts. This is similar to classes and instances in object oriented programming.

To reduce confusion, we refer to EMS labels as *marker sets* when we explicitly refer to them as semantic EMS label. A marker set is a combination of different semantic concepts called *marker*. The EMS ontology defines these markers and marker sets as concepts. The labelling adds individuals to these concepts according to the extracted marker sets.

To extract the marker and marker set instances we have to identify potential mappings between the BMS labels $\mathcal{L}$ and any marker set $\mathcal{MS}_{\mathcal{D}}$. We therefore split each label $l \in \mathcal{L}$ according to predefined separators into individual words. For the example in Table 1 we can use the underscore character and retrieve for line L1 the words: {`421`, `U6`, `RAT`} and for line L6 the words: {`S46`, `AU9`, `SUP`, `TEMP`}. These individual words are now mapped to matching marker sets.

Therefore, we combine a dictionary lookup with a linguistic similarity evaluation. The *dictionary* $\mathcal{D} : \mathcal{A} \rightarrow \mathcal{MS}_{\mathcal{D}}$ maps common acronyms $a \in \mathcal{A}$ in the building domain to marker sets $ms \in \mathcal{MS}_{\mathcal{D}}$. Our running example uses the following dictionary:

d1: `RAT` → {`Return, Air, Temperature`}

d2: `RAT` → {`Room, Air, Temperature`}

d3: `SAT` → {`Supply, Air, Temperature`}

d4: `OAT` → {`Outdoor, Air, Temperature`}

d5: `Temp` → {`Temperature`}

It specifies that `RAT` may stand for the marker set {`Return, Air, Temperature`} or {`Room, Air, Temperature`}. It also defines that `Temp` is a common acronym for `Temperature`. We automatically extend the acronym dictionary by all markers $\mathcal{M}$ in the ontology, such that they map to themselves, e. g. `Temperature` → {`Temperature`}). This includes them in the similarity computation.

The dictionary rarely contains all acronyms individual integrators use. Therefore, we compute a *string similarity* value $Q_{\mathrm{S}}(w,a)$ between each word w in the BMS label and the dictionary acronyms $a \in \mathcal{A}$ (that includes the markers). We use the Quicksilver algorithm [6] as it specializes on computing the string similarity between acronyms. We retrieve a similarity score in $[0,1]$, which is 0 if a word has no similarity to a marker and 1 if it is identical. For example, `RAT` is a full match with d1 and d2 in the dictionary and results in a similarity score of 1. `Lux` shares no letter with the above dictionary entries, but, matches the marker `Illuminance` with a score of 0.35.

We derive the similarity value $Q_{\mathrm{L}}(l,m)$ between any BMS label l and any marker m in the dictionary from this string similarity between words and acronyms. It is defined as the maximum of the similarity values from the words $w \in l$ and any acronym a for which there is a mapping to a marker set ms containing the marker m in our dictionary $\mathcal{D}$:

$$Q_{\mathrm{L}}(l,m) = \max_{w \in l, a \in \mathcal{A}} \{Q_{\mathrm{S}}(w,a) | a \rightarrow ms \wedge m \in ms\}. \quad (1)$$

This bases on the intuition, that only the strongest similarity between a word w in a label and an acronym a counts towards the correct mapping from l to m. For example, the similarity of the BMS label `U6_RAT` (line L1) to EMS label `RAT` is computed as the maximum of the similarity values Q_{S}(`U6`, `RAT`) and Q_{S}(`RAT`, `RAT`) which is 1.

Table 2 shows the similarity matrix between the BMS labels and the dictionary entries up to column d13. Each column label refers to one of the dictionary entries listed below the table. The columns d1 to d5 refer to the acronym dictionary entries and columns d6 to d13 list the extended marker

Line	BMS label	Encoded meaning		EMS Label	
		asset	semantic type	asset	semantic type
L1	U6_RAT	(Air Handling) Unit 6	Return, Air, Temperature	AHU	return, air, temperature
L2	U6_DAT	(Air Handling) Unit 6	Discharge, Air, Temperature	AHU	supply, air, temperature
L3	AHU7_RAT	Air (Handling) Unit 7	Return, Air, Temperature	AHU	return, air, temperature
L4	AHU7_SAT	Air (Handling) Unit 7	Supply, Air, Temperature	AHU	supply, air, temperature
L5	AU9_RET_TEMP	Air (Handling) Unit 9	Return, (Air,) Temperature	AHU	return, air, temperature
L6	AU9_SUP_TEMP	Air (Handling) Unit 9	Supply, (Air,) Temperature	AHU	supply, air, temperature
L7	Ext_OAT	External	Outdoor, Air, Temperature	-	outdoor, air, temperature
L8	Ext_Lux	External	Luminous Flux	-	outdoor, illuminance

Table 1. Point list example and their correct EMS label match

Line	BMS label	Acronym dictionary					Marker dictionary								EMS Label			
		d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12	d13	ARAT	ASAT	OAT	OI
L1	U6_RAT	*1.00*	1.00	0.33	0.33	*0.06*	*0.33*	*0.40*	0.38	*0.07*	*0.24*	0.27	0.26	0.24	*0.83*	0.67	0.78	0.29
L2	U6_DAT	0.33	0.33	*0.33*	0.33	*0.06*	*0.33*	0.27	0.00	*0.07*	*0.24*	*0.27*	0.26	0.24	0.33	*0.33*	0.33	0.29
L3	AHU7_RAT	*1.00*	1.00	0.33	0.33	*0.06*	*0.85*	*0.40*	0.38	*0.38*	*0.17*	0.04	0.05	0.04	*0.96*	0.80	0.78	0.19
L4	AHU7_SAT	0.33	0.33	*1.00*	0.33	*0.06*	*0.85*	0.05	0.00	*0.38*	*0.17*	*0.35*	0.05	0.04	0.80	*0.96*	0.78	0.19
L5	AU9_RET_TEMP	*0.48*	0.48	0.42	0.27	*1.00*	*0.68*	*0.75*	0.38	*0.42*	*0.70*	0.35	0.16	0.04	*0.73*	0.65	0.58	0.15
L6	AU9_SUP_TEMP	0.27	0.27	*0.42*	0.27	*1.00*	*0.68*	0.05	0.05	*0.42*	*0.70*	*0.75*	0.16	0.04	0.59	*0.71*	0.56	0.15
L7	Ext_OAT	0.33	0.33	0.33	*1.00*	0.06	0.07	0.25	0.23	*0.07*	0.04	0.00	*0.39*	0.17	0.60	0.60	*1.00*	0.59
L8	Ext_Lux	0.07	0.07	0.07	0.07	0.06	0.07	0.25	0.00	0.00	0.04	0.05	*0.05*	*0.35*	0.11	0.07	0.07	*0.21*

Dictionary:
d1: `RAT` → {`Return, Air, Temperature`}
d2: `RAT` → {`Room, Air, Temperature`}
d3: `SAT` → {`Supply, Air, Temperature`}
d4: `OAT` → {`Outdoor, Air, Temperature`}
d5: `Temp` → {`Temperature`}
d6: `AHU` → {`AHU`}

d7: `return` → {`return`}
d8: `room` → {`room`}
d9: `air` → {`air`}
d10: `temperature` → {`temperature`}
d11: `supply` → {`supply`}
d12: `outdoor` → {`outdoor`}
d13: `illumination` → {`illumination`}

EMS Labels
`ARAT` = {`AHU, Return, Air, Temperature`}
`ASAT` = {`AHU, Supply, Air, Temperature`}
`OAT` = {`Outdoor, Air, Temperature`}
`OI` = {`Outdoor, Illumination`}

italic - semantically correct mappings

Table 2. Similarity matrix between labels, the dictionary and EMS labels for the example in Table 1

dictionary. The semantically correct mappings are in italic. For line L1 the similarity is 1 for d1 and d2 as we have a full match with the word `RAT` in the BMS label. The similarity for d3 and d4 is 0.33 as a substring of `RAT` matches with the corresponding dictionary acronyms `SAT` and `OAT`, respectively. For L2 the similarity is ambiguous with 0.33 for d1–d4 and d6 as `DAT` shares the same substring with the corresponding dictionary entries. There is no direct match for L8 in the initial dictionary, however, `Lux` matches the d13 marker `Illuminance` with a score of 0.35.

The result from the dictionary matching is a mapping with similarity values from BMS labels to the marker defined by each dictionary entry. These mapping similarities need to be combined to retrieve the final similarity between the BMS label and the EMS marker set. We do this by computing the similarity value Q_{ms} between a BMS label l and any marker set ms in the EMS as arithmetic mean of the individual markers m contained in ms:

$$Q_{\mathrm{ms}}(l,ms) = \frac{1}{|ms|} \sum_{m \in ms} Q_{\mathrm{L}}(l,m). \tag{2}$$

We use the similarity value from equation 1 to ensure that the similarity is computed always from the match with the highest similarity for each marker. For example, to compute the similarity between `U6_RAT` and `ARAT` (line L1) we could consider the marker sets $\{d1,d6\}$ or $\{d6,d7,d9,d10\}$. As the similarity value of the former is higher we compute $Q_{\mathrm{ms}}(l,ms)$ based on it.

The last columns of Table 2 show the similarity values between the BMS labels and the EMS marker sets. Again, the correct ones are in italic. The similarity values for L1, L3, and L5 are highest for the mapping to `ARAT` and we have a similarity of 1 between L7 and `OAT`. Also the similarity values for line L4 and L6 are highest for the correct mapping to `ASAT`. Line L2 results in an ambiguous similarity of 0.33 with `ARAT`, `ASAT`, and `OAT` with identical values. Line L8 has a low similarity value with all EMS marker sets, but still the highest for the correct mapping to `OI`.

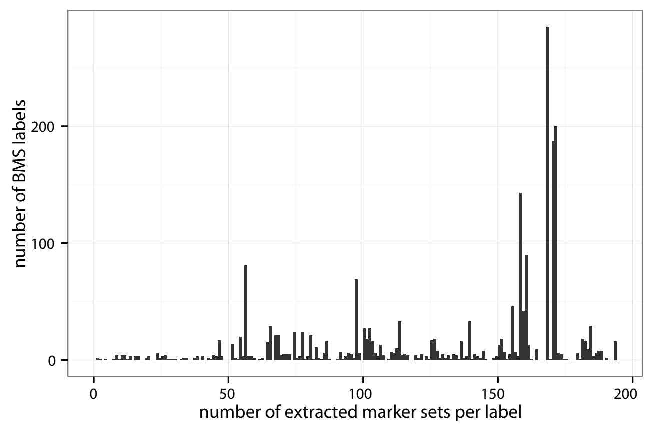

Figure 1. Histogram of the number of extracted EMS labels

4 Practical validation

We evaluated our approach using the BMS label list from the living laboratory building in Dublin which contains 2,099 labels in total. We computed the semantic similarity with a default dictionary containing 629 entries: 504 acronyms and 125 markers. It was collected from other datasets and was now applied to this test dataset for the first time. Our ontology defines 201 different EMS labels, i. e. EMS marker sets, that we seek to extract from the BMS list. The computation of the similarity values is efficient and finishes in about 25 s for on an Intel i7 4500U in a Python implementation.

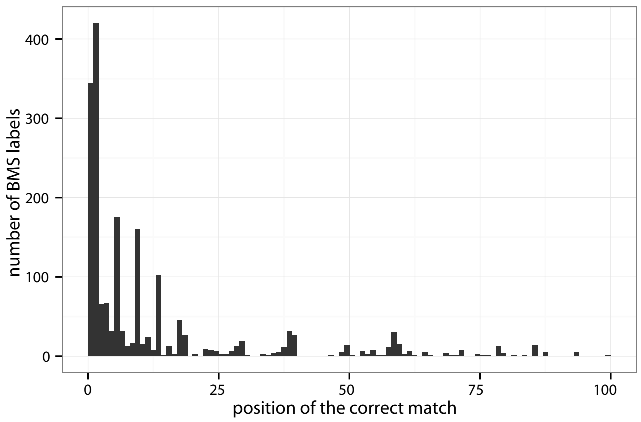

Figure 2. Histogram of the position of the correct match in the set of extracted marker sets sorted by similarity value

Figure 1 shows the histogram of the number of extracted EMS labels with a similarity $Q_{\mathrm{ms}} > 0$ per BMS label. In mean 132.6 EMS labels were extracted for each BMS label.

We now seek to evaluate whether we can further reduce the requirements for user involvement if we also take the actual similarity values between BMS and EMS labels into account. We thus considered the following question: If the user is iteratively asked to verify the correctness of the most similar EMS / BMS mapping then how many labels does he need to consider before the correct match? Figure 2 reveals a tailed asymmetric distribution for the correct match position. In mean the correct marker set is on position 15 and thus a user would have to review about 15 marker sets until he has found the correct one. Therefore, our linguistic similarity computation allows reducing the number of marker sets a user has to consider on average to 7.5 %. In 344 cases (16 %) the correct marker set has the highest similarity rating.

Finally we analyzed whether these numbers would differ if we would use other dictionaries. Table 3 compares the results for different dictionaries and shows the mean number of marker sets extracted per BMS label, the mean position of the correct match, and the number of cases in which the correct match has the highest similarity value.

If we remove all acronyms from the dictionary and match only the markers (i. e. only d6 to d13 in Table 2) then the mean position of the correct match increases to 18.7 such that a user would have to review more matches until he identified the correct one.

The number of marker sets that a user has to review drops to 8.8 if an optimized dictionary is used to which we manually added 14 dataset specific acronyms. For 584 cases (28 %) the match with the highest similarity is already correct.

Dictionary Type	Dict. Entries	Mean # Markers	Mean Pos. of Match	Highest Similarity
No Acronyms	125	122.1	18.7	368
Default	629	132.6	15.1	344
Optimized	643	131.3	8.8	584

Table 3. Experimental results with different dictionaries applied to a label set with 2,099 entries.

5 Conclusions & Future Work

We have developed a novel procedure for extracting semantic labels from textual BMS labels, which is the basis for semi-automating the deployment of energy management systems in buildings. It utilizes linguistic similarity to map textual BMS labels to semantic EMS marker sets.

Our practical experiments unveiled the pros and cons of the linguistic matching. In a realistic example, the correct match had in only 16 % of the cases the highest similarity. Therefore, the linguistic similarity does not allow an automated labelling using the highest similarity. However, the similarity values allow prioritizing the matches such that a user has to consider in mean only 7.5 % of all possible EMS labels. Future work will tackle this topic by (i) improving the accuracy of similarity estimates, and (ii) minimizing the user involvement utilizing the semantic similarity between BMS labels and marker sets.

The similarity values are the basis for a tool that semi-automates the label mapping [12] to create configurations for IBM's TRIRIGA Environmental and Energy Management Software [3]. The tool reduces the manual labelling effort from several work days to minutes. The benefits of a semantic representation of the output go beyond that and allow novel approaches for automated data analysis such as diagnosis [13].

6 References

[1] F. Baader, S. Brandt, and C. Lutz. Pushing the EL envelope. In *IJCAI*, pages 364–369, 2005.

[2] P. A. Bernstein, J. Madhavan, and E. Rahm. Generic schema matching, ten years later. *VLDB Endowment*, 4(11):695–701, 2011.

[3] N. Brady, F. Lecue, A. Schumann, and O. Verscheure. Configuring building energy management systems using knowledge encoded in building management system points lists, 2012. US20140163750 A1.

[4] J. F. Butler and R. Veelenturf. Point naming standards. *ASHRAE Journal*, B16-B20, Nov. 2010.

[5] F. Giunchiglia, P. Shvaiko, and M. Yatskevich. Semantic matching. In *Encyclopedia of Database Systems*, pages 2561–2566. Springer, 2009.

[6] H. Haller. Quikey–an efficient semantic command line. In *Knowledge Engineering and Management by the Masses*, pages 473–482. Springer, 2010.

[7] Project haystack. http://project-haystack.org, 2014.

[8] ISO 16739:2013. *Industry Foundation Classes (IFC) for data sharing in the construction and facility management industries*, Mar. 2013.

[9] ISO16484-3. *Building automation and control systems – Part 3: Functions*, 2005.

[10] W. Livingood, J. Stein, T. Considine, and C. Sloup. Review of current data exchange practices: Providing descriptive data to assist with building operations decisions. Technical Report NREL/TP-5500-50073, National Renewable Energy Laboratory, 2011.

[11] J. Ploennigs, B. Hensel, H. Dibowski, and K. Kabitzsch. BASont - a modular, adaptive building automation system ontology. In *IEEE IECON*, pages 4827–4833, 2012.

[12] J. Ploennigs, A. Schumann, and B. Chen. Demo abstract: BEAD - Building Energy Asset Discovery tool for automating smart building analytics. In *BuildSys*, 2014.

[13] J. Ploennigs, A. Schumann, and F. Lecue. Adapting semantic sensor networks for smart building diagnosis. In *ISWC - Int. Semantic Web Conf.*, 2014.

[14] P. Shvaiko and J. Euzenat. Ontology matching: state of the art and future challenges. *IEEE Trans. Knowl. Data Eng.*, 25(1):158–176, 2013.