Big Data : a tool for research.

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***Abstract*—In this document we are presenting a tool offering features of data analysis and most importantly predictive modeling in the context of building data energy management. That is a particular context but the tool can easily be adapted to any type of data environment.As of Today, the implementation is made from New-York 's John Jay Building and contains thousands of data collected from hundreds of sensors over a period of two years, and regularly updated.**

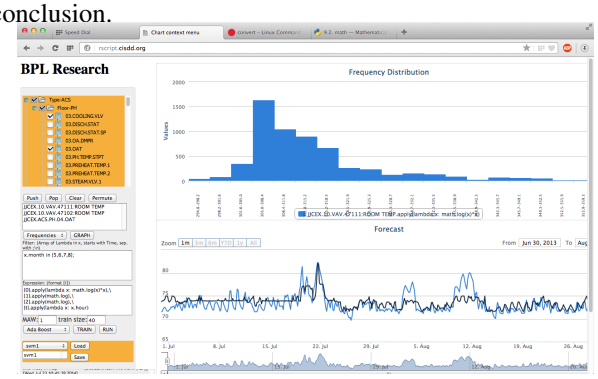
Introduction

There are many systems these days that are generating a large amount of data, some of which needs to be analyzed in real time. Data mining is now presents in every domain: marketing, finance and medical applications to name a few. Building management systems are an example of such a system. They are capable of generating in short time increments, too much for any operator to examine even retrospectively. In the mean time this mass of data is correlated, or has cycles, and sometimes has patterns or trends, upon which analysis should be based.

In this paper we will present a tool that has many features that allow aspects of the energy use in a building equipped with a modern BAS system to examine. The tool is based on open source software that can easily be used by other users for other uses.

Architecture and design have been motivated by different constraints and certainly modified several times before reaching the actual shape. Architecture sits on the following points: speed, easiness to use and share, and flexibility. We first opted for R Studio that immediatly offered points 2 and 3 but there was a bottleneck in terms of performance. We ended up building a website offering python-like concepts accessible to users.

Here we will first show the contents of this tool and possibilities of immediate achievement in terms of predictive models. Next section goes into details relative to implementation and plugin development. Section 3 presents different case studies in the domain of energy savings. This is followed by the conclusion.



I. Background (* Note * : add references ex. : NREL)

In general, Building performance energy analysis requires to handle a large number of data, from multiple sensors placed around every unit of the heating and cooling system, measuring values at a high frequency. Therefore, grouping an filtering data is necessary in order to have different views and extract behaviors of the different variables. Also, as data analysis must be done on the system dynamics, time is a very important factor. In the mean time, we know there is some cycles such as day/night, or week-end/week on which energy performance patterns are different. It is then very important to extract from data specificities during those cycles, thus to have dynamic filtering capabilities.

In addition, devices involved in energy propagation are mechanical and subject to failure. The same goes for sensor, that can without warning report wrong values. Nevertheless this failures can be detected and even anticipated with statistical tools such as moving average/moving standard deviation and autocorrelation. A building performance system should come with those features.

Energy performance models are not simple. They involve some calculations often based on derivation and integration. Plus there is so many different variables that no unique formula exists. Then analysis of complex functions is often required, for model validation or model verification. (example : neural network to modelize thermal capacity of a room).

Speaking about models, there too is no unique model that can fit every building either, not only because building location has an impact on its energy performance, but also because every building is different in terms of architecture and material i.e. thermal capacity. Other factors such as occupancy and seasonality have too a great impact on the energy model.

In existing systems, modeling is widely based on curve fitting and visual analysis of graph. Not only graphs offer at a glance a view on a large number of data, but most importantely, quickly validate or invalidate a model. Building performance analysis is the task of high level energy specialists: thus their energy models are based on differential equations. System therefore has to make possible the representation of derivatives (difference) and integration (cumulated sum), and their statistical analysis.

Last but not least, energy performance is a seasonal phenomenon with hour, day or month cycles. It is then important to extract those cycles for data analysis, through dynamic filtering.

II. Our Approach

Most of existing systems are presenting collected data under the form of a Dashboard, which will help highlighting key

features such as curve fitting, trending and why not, alerts. We wanted to follow the same direction by designing a one-page web site that would also allows sharing of work and information between reseachers.

This dashboard is articulated around three axis : Filtering and defining a data subset, building the model to analyse, and showing different statistical points of view. A fourth axis which is learning and predicting is briefly evocated here and may be the subject of another paper.

Filtering is not only the possibility to eliminate non-representative (or even biased) values, but it is mainly an easy way to reshape the time series we want to observe by first of all, accessing the different facets of a time unit such as hour, day of week, months, year, to name a few. Then it is possible to restrain the field of observations to almost any type of time 'buckets'. For example, filtering out summer data, or week-end data can be easily done.

Given the huge amount of data to be processed, we want to offer at least basic statistical tools such as correlation or moving average so a user can quickly spot a trend, a relationship between data and sometimes a dysfunctioning device. About the last point, showing the rolling standard deviation of data measured can be very useful to verify a sensor provides a correct range of values.

Graphing is the central feature of our system. Classically time series and frequency distribution are available. We added moving average/standard dev, correlation, and XY which is used to display a value against another and provides simple curve fitting for model verification. These graph are of course highly customizable, an operator being able to display any type of sensor combination.

On top of that, more elaborate mathematic transformations are available to the user through Python expressions, or formulas. That include the possibility to integrate or derive the values, combine them arithmetically, or perform a pattern detection.

Finally a new concept has been introduced, certainly still under tuning, that permit to train on and forecast data relationships. Indeed we added machine learning capabilities in order to compute efficiently complex thermodynamic events such as building response time (or thermal capacity) or the impact of the sun on the inside temperature variations. This has also another objective which is to guess 'hidden variables' such as the occupancy rate or the outside temperature.

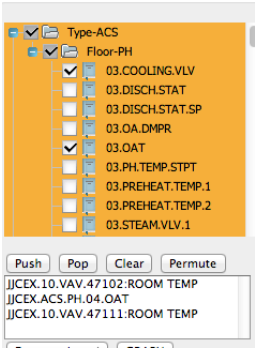
III. Dynamic Filters

One objective of this application is to provide different points of view of the entire dataset . Indeed, with millions of data collected, filtering then graphing are the best way to represent system states over time at a glance. Most importantly we want something flexible enough to accept elaborate requests.

Details of the implementation

The set of data to be analysed is simplifiable down to a table where columns are sensors' data sharing the same time axis. Prior to display, columns can be re-ordered and filtered. Graphing several sensors is then graphing the adjusted table.

Before analysis, a subset of sensors is chosen (from a tree) and each sensor is indexed for convenience (fig.1). The result is seesn as a stack of sensors on which simple operations allow stack modification : reorder, delete, add and clear.(fig.2).



Sensor indexing is implicitely made from this stack as the item on top is number 0, then number 2 . etc.

Indexing has the major advantage of simplifying input as a number is always easier to input than a long meaningless string.

From now on, sensors are designed by their index only. The final data model is then a table of time series with column #1, column #2, column #3 etc, with a special column 0 which represent the time axis.

We will later see the other advantages of such a model.

Enter into the world of Python

Behind the scene is Python which has the immense advantage of providing on-the-fly code compilation and also comes with tons of statistic and machine learning functions. Rather than building an environment from scratch and painfully design computation interfaces, we offer users an entry point inside python code. It is not necessary to know programing, just be aware of the widely documented open source Python modules. User will access a safe sandbox where they can design their own formulas.

Among the Python features available there is Pandas (ref) for the data model, and Sci-Kit for Machine Learning(ref).

Filtering with lambda functions

What is a lambda function ? Here it is simply a piece of python code embedded into an unnamed function. In other words, a lambda function takes a column of data as an input and output another column of data aligned on the time axis. The code associated to a lambda function is sent to the server that will consider it as part of the formatting process and evaluate it on-the-fly.

We have then two categories of lambda functions : boolean, and value. The first type acts as a filter and the later type as a transformation.

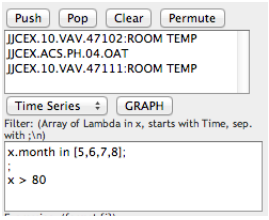
As of today, the syntax used to define lambda functions is not obvious, but this can be later wrapped into simpler code or even widgets, for a relatively small cost of development.

Filters are boolean lambda functions applied to either the time axis or each column. Graphs then display data for which the evaluation returns True.

This permits a kind of filtering based on all the usual arithmetic operations plus some Python features and also extra possibilities concerning time.

Indeed time is modelized with python object and thus offers all kind of possibilities such as weekend/weekday or leap year.

Example 1. Restrain the data set to the summer months (May, June, July,August) for which the OAT temperature reaches over 80 degrees:



Here, the first line is time filtering.

Second line is empty, third line is a condition on the second sensor (OAT) and third line is empty : no condition

A. Data transformation and formulas

Expressions have a slightly different implementation because they are not reduced to an expression per sensor but they both define the format and the value of the output. Output is a table made of a composition of input columns. Output columns are sub expressions separated with commas. For instance, if the input is composed of four sensors, the output can be any combination of one or more columns : {0}, {1} for example will define the output as only the two first sensors. Reordering is then possible.

On top of that, operations on columns are possible. We can display any type of arithmetic (in fact vector operations) on columns. For instance : {0} + {1} will display for every time tick, the sum of values from sensor 0 and 1. A mean over time can be defined as :

```
({0} + {1} + {3})/3.
```

Special index is given to the time axis, called `'{t}'`.

Furthermore transformation on sensor's individual data are made either with time series builtins or pure Python lambda expressions:

```
{0}.apply(lambda x: math.cos(x))
```

will return the cosine of sensor 0 values.

Last but not least complex operations on multiple sensors are possible, although the syntax is not yet obvious, by using the special variable 'pdata' which represents the entire data table (after filtering) :

```
pdata.apply(lambda x: x[1] + x[2] if
x[0].hour ==2 , axis =1)
```

will return sum of sensor 0 and 1 for the period from 2 am to 3 am every day.

Advanced statistic computation such as rolling functions defined in Pandas are also accessible (see pandas doc) . For instance :

```
pandas.rolling_cov({0},{1},window=4)
```

will display covariance of sensors 0 and 1 computed over a rolling period of four ticks.

ANALYSIS AT A GLANCE: TYPES OF GRAPH

To perform a good analysis it is important to have different point of views. So the application comes with :

- time serie (combined): overview over time
- XY -> relations 1
- correlations -> relations 2
- histogram -> statistics (curve shape, dispersion)
- timeserie + moving average/standard dev -> statistics (abnormal behavior)

ADVANCED FEATURES : PYTHON PLUGINS

- share work (stored on server) - complex data transformations : on timescale (row) or combining columns(sensors) - simulation possible via a math. model or a data set (or a machine) - accessible via expression box – examples: col/col, row/row , row/col

TRAINING AND PREDICTION FOR RESEARCH

advantages:

- quickly determine whether there is a relation between different measured values (on a given timeslice)
- can try different machine types, different training sets and different training size
- results can be reinjected into another expression -> model verif
- sharing of results

sits on python scikit outputs consistent with data model -> used for feedback

CASE STUDIES GO HERE

-simple case : room temp with OAT and time of day -energy propagation from emitter to sensors : SVM (add figures)

CONCLUSION

Users : researchers goals: energy savings, dysfunctionment prevention