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Research Paper

PATE (Partially adjusted thermal Enhancement) method and software for optimizing Computational Runtime in heating/cooling related simulation software (February 2022)

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ABSTRACT -*Software runtime can be very challenging in multiple industries. HVAC, cooling and heating applications are often very demanding since they involve a great amount of input and details, also several simulations of the same building or case study are often necessary before settling on an acceptable solution. In this context, this paper introduces a descision-taking python software suite thatminimizes the iterations and the required mathematical operations used in the creation of software related to solving problems of the above mentioned applications.*

INDEX TERMS – *Software runtime, machine learning, artificial intelligence,Application-Specific software, Program Execution Time, python applications.*

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I. INTRODUCTION

Even with growing computational capacities [1], software runtime is still a challenge in many industries [2]. Building HVAC simulations often require intensive amount of calculation for it usually includes a large amount of input and variables; building geometry also contributes to these computational requirements. This[3] previously published researche suggested the use of a reduced sequence of days called Short Reference Year (SRY) in which a fewer number of days(12 days often) instead of the full 365 days are used in simulation, however the same researches stated that their approach and method didn't effectively reduce the required computational time.

In the current paper Iintroduce the PATÉ (Partially Adjusted Thermal Enhancement)/SRY hybrid method which relies on simplifying the algorithm used and directly deals with the computation process in heating/cooling applications.

II. The SRY method

One of the definitions of The Short Reference Year (SRY) as described in [4] is the creation of representative days, each day is formed by hourly average of a set of days, the set can be a week, a decade (10 days) or a month (30 days) as such we get 52, 36 and 12 representative days respectively.

Using the SRY method thus constitutes of running the simulations on the representative days only instead of the full 365 days thus shortening the software runtime, results are then magnified/populated to create an artificial sequence.

III. SRY calculator

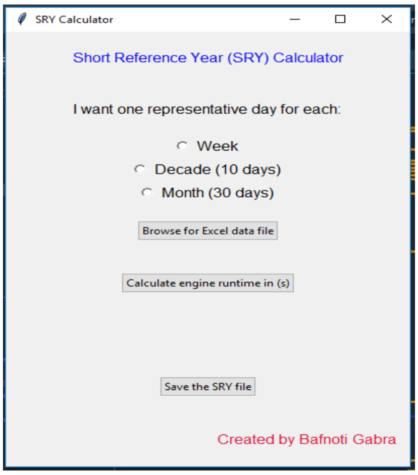

Figure 1: SRY Calculator

This is a Microsoft Windows software; it's a standalone .exe version.
The software admits any set of data, it could be the dry bulb temperature for example, the software returns the SRY set of data (hours) the user may choose one representative day for each week, decade (10 days) or month (30 days). The software equally calculates the time consumed for each calculation in seconds.
Example for an input/output calculation made on the SRY Calculator.

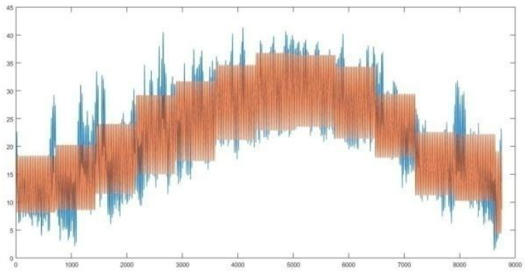

Figure 2: SRY Calculator Input (blue)/Output (red)

The software code equally allows the output (12 days in the case of our study) in the form of 288 hours or populated over the full period.

IV. Employing the SRY Calculator Output as a shortened sequence

To apply the SRY calculator to weather files, the native energyplus weather or .EPW format should be converted to an excel-readable format [.csv] once converted the metrological data deemed "unnecessary" should be removed then the modifications are carried out.
Once done, files are reconverted back to the native format .epw.
Back and forth conversions are made using the weather statistics software installed with the energy plus software suite.
An energyplus weather file features from left to right, 35 input fields, 17 of them are not used usually the most significant ones which are the temperature and solar data are left (5 fields)

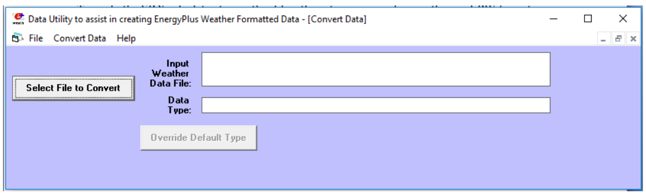

Figure 3: Eplus data converter

A 12-days-long weather file (288 hours long) is created. The shortened weather file is used for a shortened simulation. The energyplus output is then repopulated/magnified by repeating each day 30 times to create a full 8760 hours year.
For repopulation, the following tool/software was created

Figure 4: **The SRY Data Populate Engine**

V. SRY Tests

A. TEST SUBJECTS

All tests were run on an Intel core i3-3110m, 4 GB Ram laptop.
Buildings from the public domain were initially used

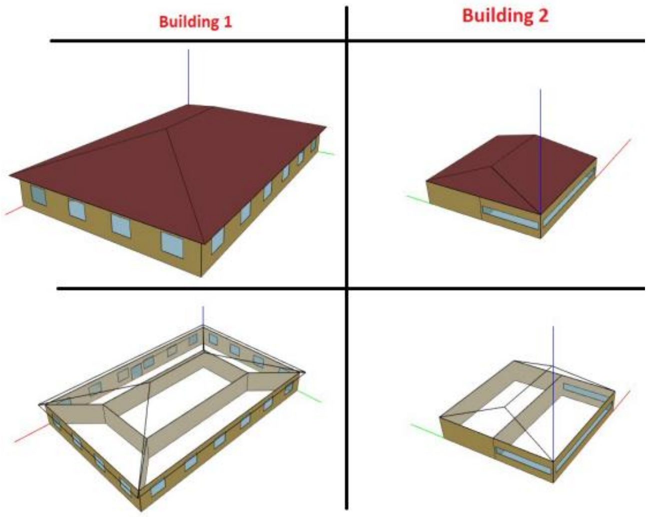

Figure 5: **Building 1 vs 2**

Building 1 features a 5 thermal zones office building while building 2 features a 2 zones fast food restaurant. Building 1 is as per the designer optimized for the city of Chicago, Illinois, USA.
Zones with the highest temperature instabilities i.e external with more air flow were chosen
To ensure the universality of the SRY method, it was applied on the previously mentioned buildings in 4 cities, Chicago, Paris, Marseille and Lyon. Cairo was eliminated for the time being for its climate is very stable compared to the above mentioned city.
The SRY method dealt with the cumulative results of heating and cooling energy demands.

Total number of tests 4 cities * 2 buildings * 2 (heating and cooling energy demands) = 16 tests though the actual number of tests is 14 since only one building was tested in the case of the city of Chicago.

B. SRY TEST, FIRST PASS 1

In this section I compared the SRY results populated over 8760 hours produced by the aforementioned software with the normal simulation results, the study included the R-squared values, as well as the average cumulative error when comparing the real vs the Software produced curves, where the average cumulative error is the average error between each respective values divided by the final real values.

Pass 1 error results can be summarized in the below table:

Table 1: Pass 1 average error results

Average building 1 heating	**5.9%**
Average building 1 cooling	**32%**
Average building 2 heating	**3.8%**
Average building 2 cooling	**13%**

With heating error averaging 4% and cooling error 18%.

C. WHAT'S WRONG WITH COOLING RESULT?

The above table represents the average of the four cities in each case. The four cities are located in relatively cold countries (3 in France and 1 in northern USA) as such the energy demands for heating is much higher than cooling, in all cases, the average method has an upper and lower limits smaller than the real signal's upper and lower limits (See fig 2) as such some cases of peak "escape" from the method and thus result in the said discrepancies, those discrepancies increase in lower demand signals because it's where the method becomes less "sensitive"

The Method also consists of populating (multiplying) the 12 days results by 30 thus any overshooting in the energy consumption will be magnified thus causing a considerable error.

D. COMPUTATIONAL TIME GAIN

In this section we compare the computation runtime taken by the energy simulation software Energyplus when running a normal full year simulation versus the time taken by the artificial shorter simulation.

Figure 6: Time consumed for a full 365 days simulation

Figure 7: Time consumed in a shortened 12 days sequence

E. SRY PASS 2

Most affected tests (worst results) were recalculated to remedy the high cooling error, this time a maximum energy was imposed to prevent overshooting, also heating was shut down during the period from May 15th to October 15th.

Pass 2 results can be found in the appendix.

F. PASS 2 RESULTS

New average error for building 1 cooling is [(6+6.5+14.5)/3]=9% (Down from 32%)

Time gain = 58.7/8.28= 7 (700%)

Repopulation takes about 0.01 second per field, as per the repopulation engine software.

G. SRY test Pass 3 (with fixed internal cooling and heating set point)

Cooling set point of 26°C and heating set point of 20°C were set, this wasn't possible with the ready-made buildings models and as such a new one thermal zone building model was created from scratch.

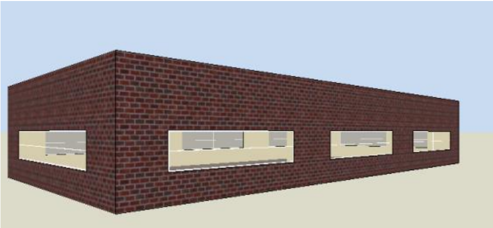

Figure 8: new building

Cooling set point of 26°C and heating set point of 20°C were set, this wasn't possible with the ready-made buildings models and as such a new one thermal zone building model was created from scratch.

Cities subject to this pass were France (Lyon, Marseille, Paris) and to give some perspective Cairo, Egypt was added.

This pass studied the heating energy, the cooling energy and the internal temperature variation.

H. PASS 3 RESULTS

As expected Cairo's average error results were the best (2% error in cooling and 3% error in heating) that's because cairo's climate is the most stable among all the study cities, naturally heating error exceeded cooling error because Cairo's cooling needs exceed Cairo's heating needs.

The opposite can be said about Lyon.

Building 3, average cities error

Cooling = 13.75%

Heating = 5.5%

Internal temperature diagram average error = 5.57%

VI. SRY Optimization - Introducing the PATÉ method

There's always a need for getting better results, that's why although the result of the average SRY method without any additions showed relatively satisfying, the following SRY optimization method were created.

The SRY method has always provided a low RSQ error (often less than 5%) but in very few cases has produced significant errors exceeding even 20%, that means that, at least, the SRY method has introduced a good "Skeleton" to work on.

PATÉ stands forPartially Adjusted Temperature Enhancement

The PATÉ Algorithm is only triggered if the relative cumulative error is higher than 5%.

Figure 9: PATÉ

I found that it's enough to remedy the high-error affected segments by "extending" or "shirking" (just like in pastry dough) their respective weather file parts. Affected segments are those who have a significantly differently slope than their real counterparts.

For example if as in the figure below we can see that the fake curve is falling off on cooling, in that case the respective weather file temperature will be extended up and up only creating a heating effect which in turn will increase the respective cooling power, to respond to this significant error phenomena and thus decrease the difference in slope between the real and software produced slope and error.

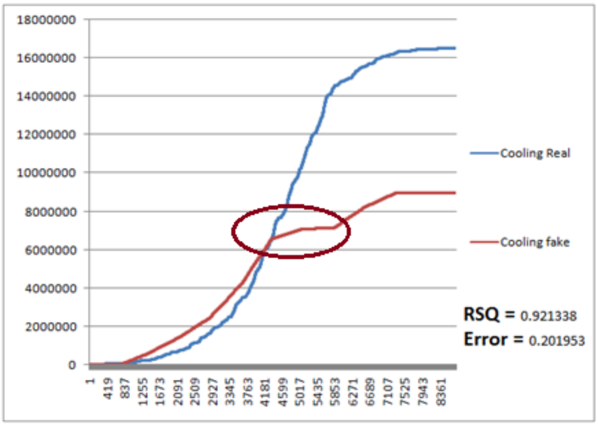

Figure 10: **Cooling error - affected segment**

A. HOW IS THE PATÉ MADE?

One simple linear equation is created

Ta=A*Tb+B

(Where Ta is the temperature after adjustment and Tb is the temperature before adjustment)

The equation is solved twice to find the 2 unknowns A and B, once on the maximum temperature value ($\boldsymbol{Tb_{max}}$) of the affected segment and another on the lower temperature value($\boldsymbol{Tb_{min}}$).

Once the A and B coefficient found, the equation is applied to the whole points of the affected segment creating a new wholly Adjusted and Enhanced Temperature-segment.

Just like any optimization algorithm, more than one iteration will often be necessary.

B. HOW ARE THE (TA)S FOUND?

$\frac{\boldsymbol{T_a}}{\boldsymbol{T_b}} = \boldsymbol{G}$, Where G is initially guessed by being the ratio between the real and artificial temperature corresponding to the maximum error in the affected segment as in the figure below

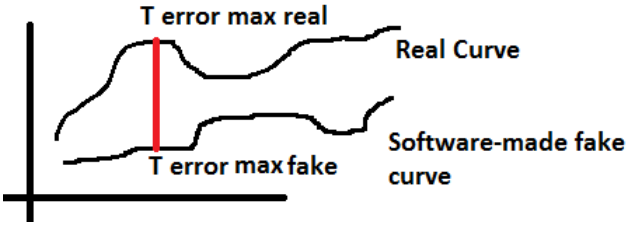

Figure 11: How to find the G factor

Next iterations of G will be calculated as the desired error multiplied by the previously used value of G divided by the obtained error.

$$G_n = \frac{G_{n-1} * desired\ error}{error_{n-1}}$$

For example a first iteration with a G of 6 yielded to an error of 15% while the desired error is 5%.
The new G will thus equals to 6*5/15=2.

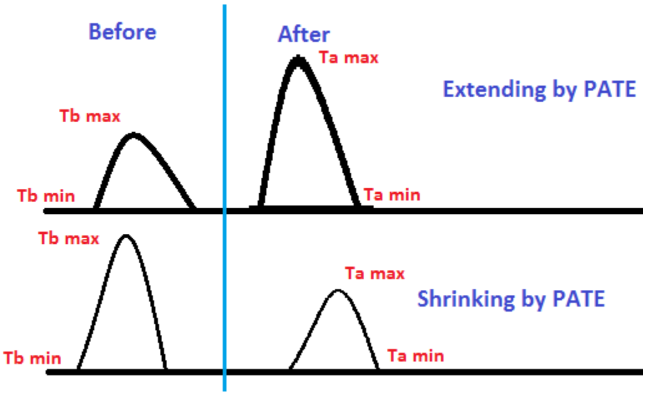

Figure 12: Extending and shrinking affected SRY Segments by PATE

VII. A simple PATÉ Algorithm

I found that optimizing the cooling and heating independently is better and simpler.
First the error is scanned then the PATE method is employed proportionally so for example if we get negative heating error it that more heating is required and thus lowering the corresponding temperature signal and vice versa, a negative cooling error means that more cooling is required, thus increasing the temperature of the corresponding temperature signal and vice versa, optimization is complete when the desired error rate is reached or when simply the algorithm is taking too much time. The optimization algorithm is rather simple compared to other optimization algorithm found in [5], [6] and [7].
Below are detailed steps of the Algorithm

1. Set the permissible maximum error
2. Scan both signals and determine affected segments by comparing the slopes of the real vs fake curve
3. Determine the error direction, field and the G factor (cooling or heating).
4. A first guess of the G factor can be made based on the error proportionality in all cases the first value could be a placeholder.
5. Find the A, B coefficient and create the linear equation
6. Translate back the populated hours to their respective SRY values/days.
7. One segment can extend over a single day or more.
8. Apply the linear equation to the whole affected segment(s)
9. Apply (copy over) the new values into their respective fields parts on the weather file
10. Run the short simulation
11. Magnify the results
12. Assess the error; the error cannot change its sign/direction, if that's the case, reverse the direction of the corrective action in the new iteration.
13. if the error is still not acceptable (in our case more than 5%) repeat the whole procedure

14. Optimization is complete if the new error is less than or equals the desired error or simply if it takes too much time just like any optimization software (runtime error)

In the following the PATE method was only applied to the dry and web bulb temperatures

VIII. PATÉ Case studies

In the following the PATE method was only applied to the dry and web bulb temperatures

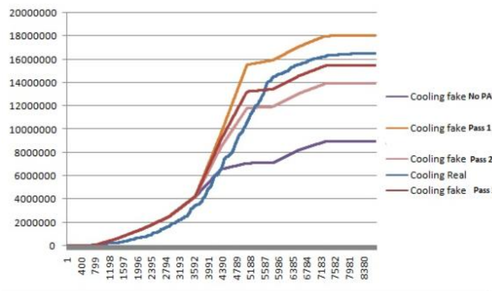

Figure 13: Paris three iterations, where the coefficient is the G factor

Paris case study needed three passes at the end of which the cooling error decreased from 20% to 6% and the heating error also decreased to 6.5%

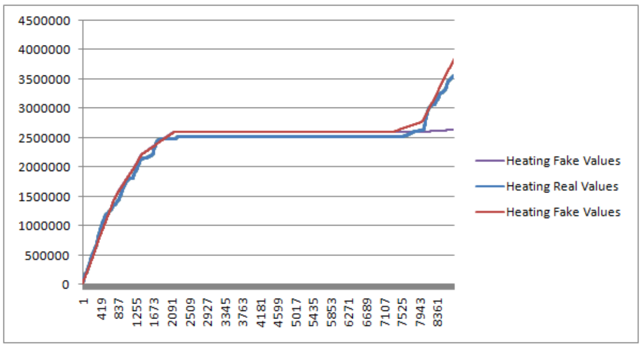

Figure 14: Cairo Case Study needed only one iteration.

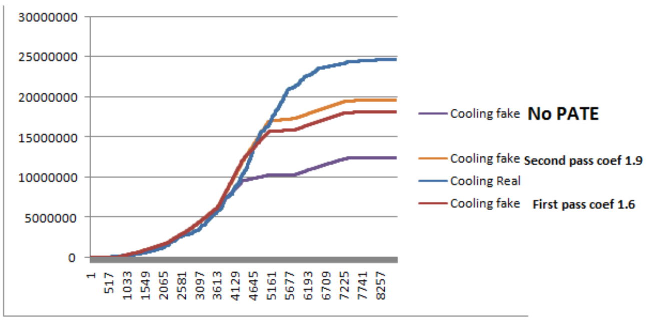

Figure 15: Lyon France Case Study - 2 iterations

For Lyon's case study, Cooling error decreased to 8.5%, and heating to 6.5%.

Based on the aforementioned algorithm, the software SRY Optomax is created

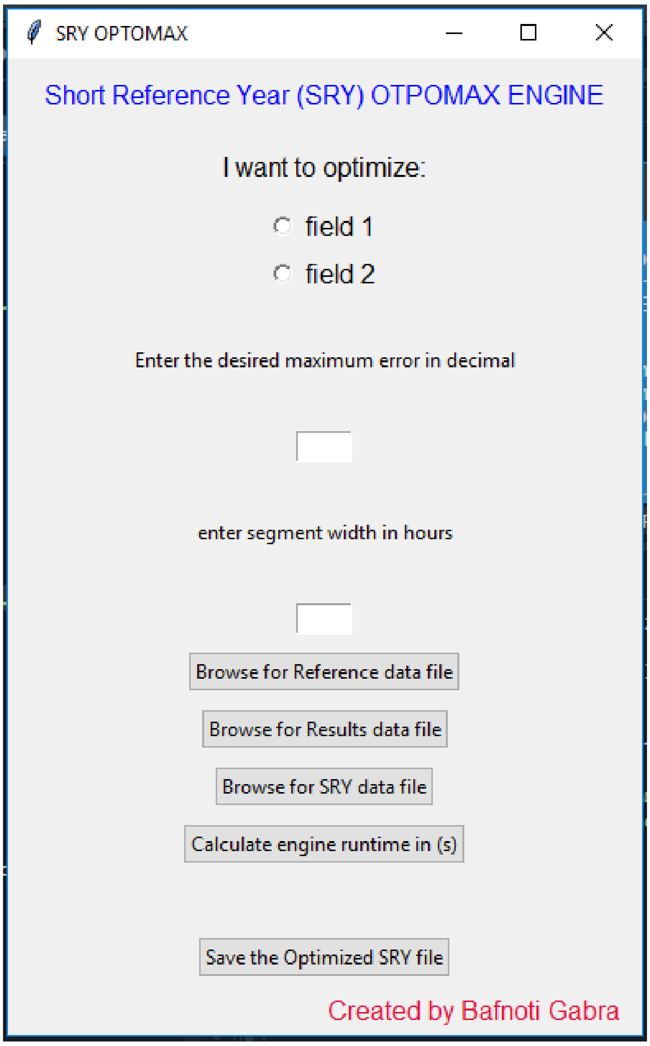

Figure 16: SRY Optomax

processing time for cases averaged around 0.04 seconds.

IX. CONCLUSION

The average-based SRY method and The PATE Optimized SRY method solved the runtime issue for the specific Heating/Cooling application.

It takes a maximum of 3 seconds to create an SRY sequence on the SRY Calculator software for one field which means a total processing time of 15 seconds for a cooling error of 5.5% (Data magnifying takes around 0.01 seconds per field).

To cover all sort of applications, the PATE Optimized SRY method is capable of bringing down errors to 6% in just three iterations. The SRY method benefits from the existing real weather file data thus shortening calculation times, directly tackles the problem of heating/cooling by introducing corrective heating/cooling actions making its effect direct and finally the equations used in the PATE method are very simple, involving very few variables.

X. Applications

The software suit may deal with other applications based on sets of hours whose variables may relate in a way similar to temperature and energy.

APPENDIX

Annex – Pass 2 results

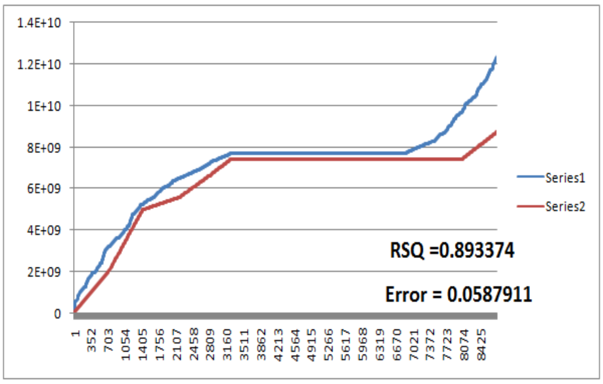

Figure 17: Heating rectified results Building 1, City of Lyon Blue data real curve, red data SRY curve

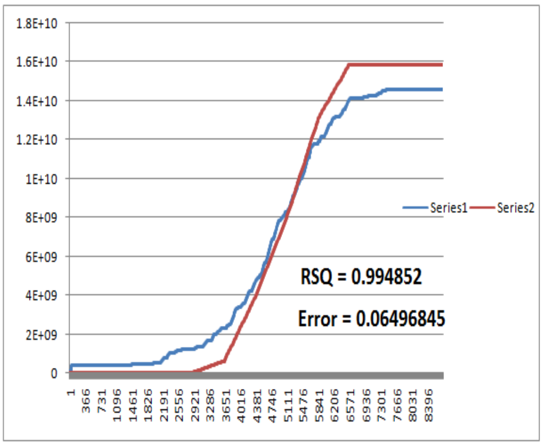

Figure 18: Rectified Result Cooling Building 1, City of 2 LyonBlue data real curve, red data SRY curve

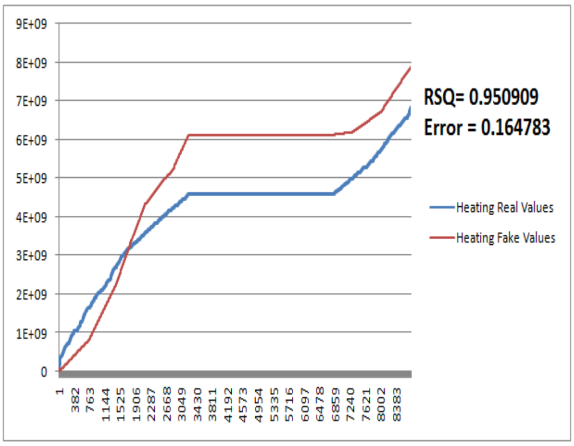

Figure 19:Figure 19: Rectified Heating result Building 1, City of Marseille

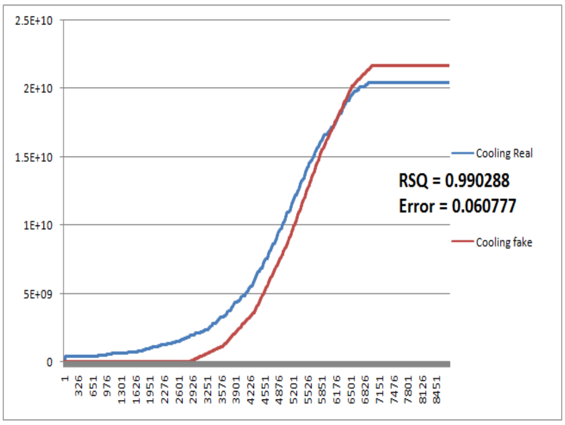

Figure 20: Rectified Results Cooling Building 1, City of Marseille

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Bafnoti held various positions in engineering and contracting companies, such as Orascom Construction and has contributed to engineering consultancies, programming, translation and technical writing projects for many projects world-wide and in several languages.