Where Did It Go? Lost Savings Found in Real-World Data

Josh Rushton and Adam Hadley, NWPCC Regional Technical Forum

ABSTRACT

This paper describes how data from NEEA's Residential Building Stock Assessment (RBSA) yields insights into residential heating energy patterns. The method is a type of calibrated simulation, but the application is different from the usual calibration exercise. While many calibrations are based on detailed models of a small number of complicated buildings or systems, our application is based on a large number of coarsely-modeled single-family homes.

The RBSA database (Baylon *et al.* 2011) provides detailed audit data for 1404 single-family homes in the Pacific Northwest. Based on this data, we use SEEM 94, a simulation engine designed to streamline energy modelling for single-family homes, to simulate heating energy for individual homes in the RBSA.

The SEEM-based estimates only know about physical building characteristics and climate, while billing-analysis estimates are entirely based on actual consumption. Interesting and quantifiable patterns emerge when the two estimates are compared for several hundred homes. These patterns help us understand why some expected savings can evade even the most thorough evaluation.

Introduction

The Northwest Power and Conservation Council's Regional Technical Forum (RTF) uses SEEM 94 to estimate energy savings due to weatherization, heating equipment, and related measures. But no model is perfect, and more importantly, we have limited knowledge of some highly-influential input parameters (especially thermostat setting, but also internal gains, infiltration, duct tightness, and others).

This problem is not new—several researchers have studied the challenges inherent in estimating residential energy savings via simulation methods (examples include Pigg and Nevius 2000; Stein and Meier 2000; Ternes and Gettings 2008; Roberts, et al. 2012). Our findings are consistent with the results of these studies. Much of our work has focused on building a coherent framework in which we can analyze the systematic differences between the modelled and observed heating energy that are associated with different building characteristics. With this framework, we can disaggregate different factors' effects and build uncertainty bounds around our estimates.

Our general approach is to use RBSA building characteristics and energy consumption data to compare SEEM-based heating energy estimates with consumption patterns observed in RBSA billing data.[1] The objective is to specify a set of standardized SEEM inputs and back-end adjustments that yield heating energy estimates that agree, on average, with actual consumption data. There are two distinct components to this research.

1 Normalized annual heating energy estimates (both electric and gas) are recorded in the RBSA. These are based on 3-parameter change point models fitted to monthly local weather data and billing data (a separate fit for each home and fuel). The fitted models are used to estimate normalized annual heating energy (both electric and gas) based on TMY3 weather data.

Phase I Calibration

To calibrate SEEM, we specify SEEM inputs—based on RBSA data when possible, and based on defined rules otherwise—and then analyze differences between SEEM- and billing data-based heating energy estimates for single-family RBSA homes. This part of the exercise is limited to homes with no off-grid heat sources and billing data showing clear heating energy signatures.[2] The result is a set of adjustments that align SEEM output with billing data (on average, for homes with clear heating energy signatures and no off-grid heat).

Phase II Adjustments for Non-Electric Fuels and Other Factors

This research examines how *electric* heating energy is affected by: (1) The presence of non-electric heat sources (natural gas and non-utility fuels), and (2) The lack of clear heating energy signatures in some homes.[3] We are particularly interested in the effects for typical *program* homes, so this analysis is limited to homes that pass a filter representing minimal program eligibility criteria. The research product is a procedure for adjusting total heating energy (for homes with clear heating energy signatures and no off-grid heat) to obtain estimates of *electric* heating energy (for program-like homes).

The two phases are entirely independent, and their results adjustment factors that apply "on top of" one-another (see *Application*, below. Together, they yield a complete method for deriving SEEM-based electric heating energy estimates for program-like homes.

Highlights. Our analysis shows that, relative to homes that are cheap to heat, homes that are expensive to heat (whether due to poor insulation, a cold climate, or an expensive heat source) tend to use less heating than expected from their physical characteristics alone. This is consistent with the findings of other researchers:

- (Pigg and Nevius, 2000, page iv): "…we found that the home energy rating system…overestimates heating energy use on average. For most homes the overestimate is moderate…, but the overestimate is substantial for inefficient homes..."
- (Polly, Kruis, and Roberts, 2011, page 3): "Multiple studies confirm that analysis methods tend to over-predict energy use and savings in poorly insulated, leaky homes with older mechanical systems…"
- (Roberts, et al, 2012, page 29): Table 8 shows that the difference between predicted and measured gas usage tends to be higher—predicted minus measured tends to be more positive/less negative—for homes with poorly-insulated walls and/or ceilings and less efficient heating systems. In other words, the model tends to over-predict energy consumption in these homes.

[2] To obtain the calibration sample, we filtered the RBSA sample to isolate homes with (1) no indication of non-utility heating fuel (wood, pellets, propane, oil) in any RBSA data field; (2) reasonably reliable billing analysis fits, and (3) billing energy estimates of at least 1500 kWh (electric and gas combined). The calibration report (RTF 2013a) describes these filters in detail.

[3] Homes with high heating energy use tend to have clear heating energy signatures. Thus, phase-I-calibrated SEEM kWh tends to overestimate heating energy for any population that includes homes with weak heating energy signatures.

We do not need a study to tell us that some people turn down their thermostats in the face of high heating bills.[4] But quantifying the effect is another matter, and the cited studies all derive quantitative estimates in their respective contexts. The present study contributes estimates in the SEEM/RBSA context to the literature. It also provides a calibration framework that we find to be coherent, flexible, and reasonably comprehensive. With this framework, we can estimate the magnitude of the effect as a function of climate and building characteristics, and we can estimate the extent to which electric heating energy is affected by non-electric fuel sources and poor heating energy signatures. We also provide error bounds for all of our estimates.

With these results, we can explain why some expected savings do not materialize as load reductions on the grid. It is important to note that these findings come with a caveat: To our knowledge, no research to date, including ours, has quantified the extent to which this kind of take-back actually *causes* the discrepancies between modeled and measured results. However, the same pattern has been observed in multiple investigations, and it has been consistent across different housing samples and different simulation models. Furthermore, in the course of our investigation we devised tests to check for alternative causes where possible.[5] And finally, a non-causal relationship would not explain low realization rates in evaluated weatherization programs.

Analysis and Results

As noted above, the patterns observed in this calibration make sense in terms of economically-driven heating behaviors—poorly-insulated homes tend to exhibit less heating energy than SEEM (69/64), and this effect is more pronounced in homes that use expensive heat sources or reside in cold climates. Though we do not claim to have proven a *causal* relationship, we have found that thermostat adjustment arguments can explain most of our results. In what follows, we note that certain patterns are consistent with natural cost-sensitive heating decisions, but we generally stop short of actually asserting causality. Many of our results are descriptive—they are not concerned with causality—but causality is important to the logic of our savings calculations (see *Applications*, below).

Basic Ingredients

SEEM-based energy estimates. The first step in our analysis is the development of a set of SEEM inputs for the RBSA sample of homes. Most inputs for physical characteristics are explicitly recorded in the RBSA database (wall insulation, window properties, foundation type, etc.), but other inputs (such as internal gains and thermostat schedules) are specified by procedures developed by a committee of experts. These inputs and procedures are all documented in a publically available workbook (RTF 2013c). Importantly, all SEEM runs in this study used a daytime thermostat setting of 69° F and a nighttime setback to 64° F. As a reminder

[4] Some portion of the tendency may be due to some un-observed variables, such as socioeconomic status, that are correlated with the observed envelope or heat source variables. However, such explanations may not explain low realization rates in pre-/post- studies.

[5] For example, we saw the same basic pattern when we limited our analysis to homes for which actual blower-door test data was input into SEEM. This tells us that the problem is not caused by unknown infiltration trends. A similar test based on duct-blaster data led to the same conclusion for duct tightness.

that Phase I results are specific to these inputs, we refer to SEEM heating energy estimates as *SEEM 69/64 heating energy* or simply *SEEM 69/64*.[6]

Billing-analysis energy estimates. The billing analysis uses a variable-base degree-day (VBDD) algorithm to fit each site's billing data to local weather data. *Variable base* refers to the fact cooling-degree days and heating-degree days are calculated under a range of possible bases and billing data is fit to each possibility. The regression with the highest R^2 is designated the VBDD fit, and annualized heating energy is derived from this model.

The RBSA provides annualized VBDD estimates for both gas and electric heating energy. We refer to the electric estimate as *VBDD kWh*, the gas estimate as *VBDD therm*, and their sum as *VBDD heating energy* or simply *VBDD*.[7]

Phase I: Total Heating Energy

The phase I objective is to identify and quantify systematic trends in the percent differences between SEEM 69/64 and VBDD. The analysis sample is restricted to homes with no supplemental heat and strong heating energy signatures. For these homes, VBDD gives reasonable—but noisy—estimates of total heating energy.

We use regression to quantify patterns in the percent differences between SEEM 69/64 and VBDD. Our final model includes four explanatory variables. There are two climate zone indicator variables, one indicator for heating system type (electric resistance versus gas or heat pump), and a variable that quantifies heat loss. The results are presented in Table **1**.

Table 1. Phase I regression results

	Coefficient	Standard Error	P-value
Intercept	-0.62	0.07	0.000
Heating Zone 2	0.15	0.06	0.008
Heating Zone 3	0.31	0.08	0.000
Electric Resistance	0.25	0.04	0.000
U-variable	4.45	0.51	0.000

Adjusted R^2 = 24%

To see what this is telling us, consider a home in Zone 2 with electric resistance heat and envelope characteristics that yield a value of 0.075 for the U-variable. For this home, the model yields $\hat{y} = -0.62 + 0.15\times1 + 0.31\times0 + 0.25\times1 + 4.45\times0.075 = 0.114$. This says that for such a home, SEEM 69/64 tends to over-estimate VBDD by about 11.4%. Therefore, the phase-I-calibrated SEEM heating energy estimate is SEEM 69/64 × $1/(1+\hat{y})$ = SEEM 69/64 × 1/1.114. The value $1/(1+\hat{y})$ is called the phase-I adjustment factor.

We describe the regression variables in detail below. For now, we note that the signs on the coefficients (all positive) tell us that SEEM 69/64 tends to *exceed* VBDD in colder climates, in poorly-insulated homes (with higher heat loss rates), and in homes with electrical-resistance

[6] Our results are generally expressed as percent adjustments to SEEM 69/64. Energy units are not relevant to these expressions, and we omit physical energy units (typically kWh) when there is no ambiguity.

[7] RBSA homes have a mix of natural gas and electric heat, but the comparisons in Phase I require a common energy unit. We use kWh as the common unit, and convert therms into kWh as needed. As with SEEM 69/64, the physical units themselves are usually not important so we leave them out when this does not create ambiguity.

heat. In other words, these homes are associated with larger ŷ values, and *smaller* adjustment factors. Since SEEM 69/64 inputs do not capture any behavioral conservation efforts, the effects captured in the model could all be explained by the fact that people conserve heat when heating costs are high.

Explanatory variables in the phase I model are defined as follows:

$$I_{\text{Heating zone 2}}(x) = \begin{cases} 1 & \text{if home } x \text{ is in heating zone 2 } (6000 < \text{HDD}_{65} \leq 7500); \\ 0 & \text{otherwise.} \end{cases}$$

$$I_{\text{Heating zone 3}}(x) = \begin{cases} 1 & \text{if home } x \text{ is in heating zone 3 } (7500 < \text{HDD}_{65}); \\ 0 & \text{otherwise.} \end{cases}$$

$$I_{\text{Electric Res.}}(x) = \begin{cases} 1 & \text{if the primary heat source in home } x \text{ is electric resistance;} \\ 0 & \text{if the primary heat source is a natural gas furnace or heat pump} \end{cases}$$

$$\widetilde{U}_0(x) = \begin{cases} U_0(x) & \text{if } U_0(x) \text{ is below the zone-}i\text{ cut-off, } c_i \ (i = 1, 2, \text{or } 3); \\ c_i & \text{otherwise.} \end{cases}$$

Here, $U_0(x)$ is the total heat loss rate (Btu per °F-hour-ft^2, including both infiltration and conductive losses through all surfaces), divided by the total surface area of the house (in square-feet). The heat loss variable $\widetilde{U}_0$ is tailored to reflect the heat-loss trend observed in the data (based on the data itself and the residuals of partial models).

The variables in our model (and many others) are included in SEEM input and their direct physical effects are accounted for in the SEEM simulations. We emphasize that some stock inputs (e.g., thermostat setting) are only approximations to the actual parameters, and our goal is to identify and correct any systematic errors that may result from biased input parameters. In principle, almost any SEEM input is a candidate for describing percent differences between SEEM 69/64 and VBDD, but most do not actually correlate with any observed trend. The variables in our model account for all systematic trends we were able to identify.

Finally, the adjusted R^2 value must be interpreted in right context: The model seeks to explain deviations between VBDD and SEEM69/64, and it is able to explain 24% of the variability in these deviations. Since SEEM69/64 cannot account for behavioral patterns or highly detailed site characteristics, we know that some degree of variability is unavoidable. To interpret the R^2 value we must therefore ask how much of this variability one should expect to explain with a regression model. But *a priori,* there is no reason to expect that the site characteristics will explain *any* of the variability since SEEM69/64 already takes site characteristics into account. As a result, it is difficult to say whether 24% is a desirable value.

Phase II: Electric Heating Energy, Supplemental Fuels, and other Factors

The objective is a method that takes total heating energy estimates for homes with clear heating energy signatures and adjusts them to obtain *electric* heating energy estimates for typical program-eligible homes. We are particularly interested in understanding how electric heating energy is affected by the presence of non-electric heat sources (natural gas, wood, propane, etc.). When we apply these adjustments to phase-I energy estimates—those refer to total heating energy in homes with clear heating energy signatures—we obtain *electric* heating energy estimates for "program-like" homes. To limit bias, we also check how electric heating energy is affected by the various data filters that differentiate the phase I sample from "program-like" homes.

Although the results are ultimately applied to energy estimates derived from SEEM 69/64, the phase II research question—*How is kWh affected by other fuels and sample filters?*—actually has nothing to do with SEEM *per se*. As in phase I, we use regression to quantify the effects of interest. But this time, the regression is set up to describe how different factors generate percent changes in VDBB kWh. SEEM does not arise in the phase II analysis.

Since we are particularly interested in electric heating kWh for program-eligible homes, we fit the model to the subset of RBSA homes that satisfy criteria[8] designed to reflect a minimal program eligibility screen. This restriction ensures that the dynamics captured in the regression describe how the different factors affect heating kWh for program homes.

To control for potentially confounding variables, our model includes some explanatory variables found to drive variations in heating energy but whose effects are not of direct interest. These relate to climate, thermal envelope properties, house size, and type of electric heating equipment.

Table 2. Phase II regression results

	Coefficient	Standard Error	P-value
Intercept	-0.068	1.03	0.947
ln(UA×HDD)	0.329	0.09	0.000
ln(Sq. ft.)	0.575	0.10	0.000
Heat pump	-0.415	0.08	0.000
Elec. FAF	0.172	0.09	0.049
Off-grid high	-0.625	0.13	0.000
Off-grid medium, Zone 1	-0.217	0.08	0.010
Gas heat high	-1.039	0.11	0.000
Phase I Bill Filter	-0.423	0.11	0.000

Two of the explanatory variables involve natural logarithms, and the y-variable is logged as well (y = ln(VBDD kWh)). This is done to frame the problem in terms of percent changes. This is a common procedure described in any textbook on regression modeling or econometrics, so we do not discuss its justification here. Instead, we focus on describing what the results mean.

The coefficients for the logged terms, ln(UA×HDD) and ln(Sq. ft.), express *elasticity*: A 1% increase in the product UA×HDD is associated with a 0.33% increase in VBDD kWh;[9] likewise, a 1% increase square-footage is associated with a 0.58% increase in VBDD kWh.[10] The remaining variables are all coded as indicators (one when the factor applies, and zero when it does not). These variables' coefficients are interpreted as approximate percent changes in VBDD kWh associated with each factor. Thus, all else being equal, having an electric forced air furnace

[8] The criteria are these: (1) The home must have some permanently-installed electric heating equipment; and (2) The home may have no disqualifying equipment (gas FAF, gas boiler, oil FAF, or oil boiler).

[9] UA is the home's conductive heat loss rate (expressed in Btu per °F-hour). The explanatory variable ln(UA×HDD) uses base-65 heating degree days—it does not use the house-specific bases generated in the VBDD analysis. Since actual balance points tend to be lower than 65° F, and since the phase-II regression uses a heat loss rate that does not include infiltration losses, one should not expect a 1% increase in heating energy for a 1% increase in UA×HDD.

[10] Naturally, UA×HDD and square footage are correlated, but the correlation is not strong enough to yield an unstable fit (which would typically reveal itself in the standard errors). In any event, these variables' effects are not of direct interest at this phase of the calibration—they are only included in the model so that the regression does not attribute any of their effects to the variables of interest.

(rather than baseboard heat)[11] is associated with an increase in VBDD kWh of approximately 17% (the actual estimate is exp{0.17} – 1 = 19%). Most of the regression variables are self-explanatory; the exceptions are as follows:

$$I_{\text{Off.Grid.High}}(x) = \begin{cases} 1 & \text{if home } x \text{ has over 40 MBtu in reported off-grid heat;} \\ 0 & \text{otherwise.} \end{cases}$$

$$I_{\text{Off.Grid.Med.Z1}}(x) = \begin{cases} 1 & \text{if home } x \text{ is in zone 1 and has 5-40 MBtu in reported off-grid heat;} \\ 0 & \text{otherwise.} \end{cases}$$

$$I_{\text{Gas.Heat.High}}(x) = \begin{cases} 1 & \text{if home } x \text{ has over 5,000 kWh in estimated gas heat;} \\ 0 & \text{otherwise.} \end{cases}$$

These variables are noteworthy for their bluntness—as descriptions of non-electric fuel usage they are extremely coarse. This is a deliberate response to the fact that these variables' true values are uncertain, and their effects on VBDD kWh are highly variable and cannot be captured with much precision. Indicator variables only capture differences among group averages, and attempts to capture finer detail proved instable.

The last variable in the regression indicates whether a house was screened out of the phase-I analysis by the billing data filter. This variable's negative coefficient tells us that these houses tend to have lower average VBDD estimates, as one would expect.

As mentioned above, the effects of UA×HDD, square footage, and equipment type are all accounted for in SEEM (calibrated per phase I). Thus we have no direct interest in these variables at this stage of the analysis—they are only included in the regression so they will not confound our estimation of the other variables' effects. The remaining variables capture the effects we are after—the decrease in VBDD kWh associated with high levels of non-electric heating fuels and not finding a strong heating signature in the VBDD analysis.

Phase II net results. The effects captured in the phase II regression need to be pro-prated to account for the rate at which the different factors occur in the target population. The net average adjustment is close, but not equal, to the percent change in VBDD kWh implied by the regression model with inputs pro-rated to reflect the rate of occurrence of each factor of interest. (The difference is due to nonlinearity of the log function.) The RTF determined that the tedious and error-prone calculations needed for exact mathematical correctness on this point are not worthwhile given the error bounds inherent in the calibration exercise. We developed a simplified procedure (RTF 2013b) to streamline RTF applications.

Table 3 presents the net adjustments obtained through the simplified procedure. The unmodified adjustment for each factor is just the factor's affect per affected home, times the percent of homes affected. The final adjustments are similar, but not equal, to the unmodified adjustments.

[11] The Phase II sample is intended to reflect "program-like" homes. One of the filters used to define the sample is that the home must have a permanently-installed electric heat source (baseboard, furnace, or heat pump). Since the model includes indicator variables for electric furnace and heat pump, those variables' effects are relative to the baseboard case.

Table 3. Net phase II adjustments for heating zone 1

	KWh adjustment for each affected home	Percent of heating zone 1 homes affected	Net average adjustment, unmodified*	Net average adjustment, final**
Off-grid high	-46.5%	9.6%	-4.5%	-4.2%
Off-grid med (Z1)	-19.5%	28.7%	-5.6%	-5.2%
Gas heat high	-64.6%	7.1%	-4.6%	-4.3%
SEEM Bill Filter	-34.5%	19.7%	-6.8%	-6.3%
Zero kWh	-100.0%	5.3%	-5.3%	-5.3%
Total	NA	NA	NA	-25.2%

* The factors are not independent, so there is no simple way to combine the unmodified adjustments to obtain single composite adjustment.
** The final adjustments have been scaled so that their sum equals the overall adjustment that is correct per the RBSA sample.

The zero-kWh adjustment in Table 3 is due to the fact that the VBDD analysis found no heating energy for some homes in the phase II sample. These sites were not included in the regression (the natural log of zero is undefined), so we make a separate adjustment to account for these homes in the population. Together, the zero-kWh and bill-filter adjustments account for homes whose bills reveal little heating energy use (as examples, this can occur when a home has limited occupancy during the heating season, or if the home simply has “noisy” bills that defy VBDD analysis).

Some programs may apply more stringent eligibility restraints than our “minimal” criteria. Our analysis is intended to accommodate such programs to the extent possible. For example, a zone-2 weatherization program that only serves customers with high heating energy may be able to justify a more modest adjustment since the bill-filter and zero-kWh factors do not apply to their population.

Application: Putting It All Together

Using the results of phases I and II, we estimate average heating energy for a prototypical home in 3 steps:

1) Use the prototype’s physical characteristics to develop SEEM inputs and run SEEM with these inputs (and 69 day/64 night t-stat settings) to obtain SEEM 69/64.
2) Apply phase I adjustments to total heating energy for the prototype:
   a) Use the home’s envelope characteristics to evaluate the U-variable;
   b) Use the coefficients in Table **1** with the U-variable, heating zone, and heat source to estimate the phase I adjustment factor, A_1;[12]
   c) The total heating energy estimate is SEEM 69/64 × A_1.
3) Apply phase II adjustments to estimate electric heating energy for program-like homes similar to the prototype:

[12] The adjustment is close, but not equal, to the percent difference estimated by the regression model. The gap results from the way we constructed the percent difference variable used in the Phase I regression model. For reasons beyond the scope of this paper, we used y = (SEEM – VBDD)/[(SEEM + VBDD)/2], and this expression must be “unwound” to obtain adjustments that apply directly to SEEM 69/64. See (RTF 2013a) for details.

a) Estimate the rate of occurrence of different levels of non-utility fuels and weak heating energy signatures in the target program population;[13]
b) Use these rates and the coefficients in Table 2 to obtain the phase II adjustment factor, A_2;
c) Electric heating energy for the prototype is estimated as: SEEM 69/64 × A_1 × A_2.

To estimate savings, we apply this procedure separately to the base-case and efficient-case prototypes.

Both phases of the calibration tend to reduce measure savings estimates relative to uncalibrated SEEM estimates. The phase-I adjustment factor is increased when a home's envelope is improved (a lower U-value decreases the $\hat{y}$ value, which yields a higher adjustment factor). Therefore, the Phase-I adjustment tends to increase efficient-case energy estimates relative to base-case estimates. The phase-II adjustment factor does not change between efficient- and base-cases, but it is always less 100%, so it reduces all estimates—efficient-case, base-case, and savings—by a fixed percentage.

Conclusions

Both phases of the calibration tend to reduce measure savings estimates relative to uncalibrated SEEM estimates. The phase-I adjustment factor is increased when a home's envelope is improved (a lower U-value decreases the $\hat{y}$ value, which yields a higher adjustment factor). Therefore, the phase-I adjustment tends to increase efficient-case energy estimates relative to base-case estimates. The phase-II adjustment factor does not change between efficient- and base-cases, but it is always less 100%, so it reduces all estimates—efficient-case, base-case, and savings—by a fixed percentage. These reductions may actually be benefits in themselves, as some authors have expressed concern about the potential consequences of optimistic savings estimates and the low realization rates they lead to (e.g., Stein and Meier 2000; Ternes and Gettings 2008). In any event, our goal must be to provide the most accurate estimates we can, whether they are higher or lower than what we previously thought.

We mentioned at the outset that our work has focused on building a coherent framework for analyzing the systematic errors in SEEM 69/64 estimates. Our regression-based framework lets us use standard analytical methods to understand uncertainty and to control for confounding variables.

Finally, note that with most regressions, there is no single best model specification. The models we present capture the main effects we are after in a manner that is tailored to the RTF's needs. For example, the phase-I regression (see Table **1**) captures the effect of envelope quality in a single continuous heat-loss variable. This leads the model to treat heat loss through all different paths in a uniform manner. Component-specific variables (e.g., one variable for wall insulation, another for ceiling insulation, etc.) would not be able to capture any effect due to minor heat loss paths. Another example is the disaggregation of effects in phase II (see Table 2). By splitting the phase-II adjustment into separate components, we provide a basis for utilities to use eligibility screens to improve savings.

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[13] The RTF uses the RBSA to estimate these rates by heating zone.

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