Performance curves for high SEER ductless mini/multi-split heat pumps

Prepared by Solaris Technical, 2020-10-08. Last updated 2020-10-20.

The driver for this project is the presence of residential ductless split system products on the market at high SEER levels (19 and above). However, the DEER residential prototypes (up through DEER2020/MASControl3) lack data and model inputs specific SEER 19 and above, and it does not seem justified to use the existing DEER assumptions based on products with SEER 18 and lower. So, it is desired to be able to model the savings for these higher SEER products in a manner consistent with the modeling approach used for other residential HVAC workpapers. Since the DEER residential prototypes use eQUEST/DOE2, some of the key pieces of information used in the model setup for HVAC equipment are: nominal energy input ratio (EIR for cooling and HIR for heating modes); and performance curves that account for departure of capacity and energy input ratio from rated values at rated conditions, as a function of temperature and part load ratio. These eQUEST/DOE2 inputs are not directly listed in product ratings (and in fact, SEER is never used in the model). Also note that the eQUEST/DOE2 modeling approach via these performance curves cannot exactly match product performance across different conditions. Thus, the intended results from this project are:

* Identify product segments (defined by capacity range and SEER range) that would represent reasonable measure offerings, i.e. products within each segment have similar performance, and each segment includes a reasonable share of available products (per AHRI database).
* For each measure offering, assign representative values for EIR and HIR (per AHRI database)
* Develop performance curves from product data, and for each measure offering assign the representative product/performance curves (per manufacturers’ data)

# Product segments (capacity, SEER rating)

We downloaded approximately 9,000 product entries from the AHRI database for residential, variable speed, mini-split or multi-split heat pumps. Some of these products were labeled as “ducted indoor units”, and some products are duplicated with all the different brands offered by the manufacturer.

As will be discussed later, we observed that performance curves were characteristically different for products in <36 kBtu/h and >= 36 kBtu/h capacity ranges. We started by segmenting products by these categories.

After filtering out ducted systems and duplicate entries, we looked at the relative frequencies of product entries by SEER, within each capacity range.[[1]](#footnote-1) In the low capacity category, we found a number of products in each SEER bin up to 23, but few products at 24+. In the high capacity category, we found a number of products in each SEER bin up to 22, but few products at 23+.

Thus we propose to segment products into these measure offerings or tiers:

* < 36 kBtu/h cooling capacity, SEER 19
* < 36 kBtu/h cooling capacity, SEER 20
* < 36 kBtu/h cooling capacity, SEER 21
* < 36 kBtu/h cooling capacity, SEER 22
* < 36 kBtu/h cooling capacity, SEER 23 and above
* >= 36 kBtu/h cooling capacity, SEER 19
* >= 36 kBtu/h cooling capacity, SEER 20
* >= 36 kBtu/h cooling capacity, SEER 21
* >= 36 kBtu/h cooling capacity, SEER 22 and above

# Typical EER and HSPF by segment

EIR and HIR inputs to eQUEST/DOE2 can be calculated directly from EER and HSPF product ratings, but note that these rated values apply only at rated conditions (indoor/outdoor temperatures and full output). As discussed in the next section, the number of products for which we had full data (as used for performance curves) was small, just ten products. This did not seem sufficient quantity of data to establish the average EER and HSPF in each larger market segment. We again turned to the AHRI product database, which contains a large sample of products.

First, we tried to fit the trends for each size category with a simple quadratic trend. However, there is a large amount of variation between products at any given SEER level. Therefore, it seems important to look at the individual product segments (SEER bins), and calculate the average (mean) of 1/EER. We don’t need a smooth trend for this; in fact, because EER is not the only factor that determines SEER, it is even possible that the “average” trend does not show a steady increase of EER for each SEER point increase. So we propose to use these product segment averages directly for the energy models.

To summarize, the average EER and HSPF values by segment:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Offering / Tier | Segment | EER | HSPF | EIR | HIR |
| 1 | < 36 kBtu/h cooling capacity, SEER 19 | 11.5 | 10.2 | 0.29543 | 0.33375 |
| 2 | < 36 kBtu/h cooling capacity, SEER 20 | 12.4 | 10.5 | 0.27580 | 0.32347 |
| 3 | < 36 kBtu/h cooling capacity, SEER 21 | 12.7 | 10.6 | 0.26781 | 0.32194 |
| 4 | < 36 kBtu/h cooling capacity, SEER 22 | 12.8 | 10.7 | 0.26553 | 0.31752 |
| 5 | < 36 kBtu/h cooling capacity, SEER 23 and above | 14.2 | 11.6 | 0.24106 | 0.29381 |
| 6 | >= 36 kBtu/h cooling capacity, SEER 19 | 11.5 | 10.3 | 0.29671 | 0.33134 |
| 7 | >= 36 kBtu/h cooling capacity, SEER 20 | 12.0 | 10.8 | 0.28441 | 0.31617 |
| 8 | >= 36 kBtu/h cooling capacity, SEER 21 | 12.0 | 10.5 | 0.28463 | 0.32472 |
| 9 | >= 36 kBtu/h cooling capacity, SEER 22 and above | 12.4 | 10.6 | 0.27537 | 0.32040 |

Immediately, we can anticipate that offering #8 is not very attractive unless there is a significant difference in performance curves: in the high capacity range, on average, SEER 20.0-20.9 products (N=99) outperform SEER 21.0-21.9 products (N=117) in terms of HSPF, and perform the same in terms of EER.

# Performance curves

The workpaper development team (Solaris and SCE) reached out to several manufacturers of ductless mini-split and multi-split heat pumps to request data that could be used to create eQUEST models of these systems, including performance curves.

* Mitsubishi
* Trane
* Fujitsu
* LG
* Daikin
* Carrier

Carrier provided a sample data sheet with rated cooling and power input over a range of temperature conditions, but no part load performance information; it was determined not to model this product without the part load performance data. Daikin provides for several of its VRV systems an eQUEST modeling library. However, it was determined that this data does not represent the target equipment type. Mitsubishi provided data in spreadsheet format for 10 models, covering performance under rated conditions as well as capacity output and power input over a range of temperature conditions and compressor speeds,[[2]](#footnote-2) for both cooling and heating mode. This was determined to be sufficient data to model these performance curves in eQUEST:

* COOL-CAP-FT (and MIN-UNLOAD-RATIO)
* COOL-EIR-FT
* COOL-EIR-FPLR
* HEAT-CAP-FT
* HEAT-EIR-FT
* HEAT-EIR-FPLR

We were not able to obtain data from which to evaluate cycling loss performance curve (when loads are below minimum unloaded capacity for continuous operation, and unit cycles on/off to meet loads). However, the SEER 19+ systems under consideration are typically variable speed systems (per discussion with manufacturers) that can unload down to a relatively low load ratio without cycling (such as 30%), so the cycling loss performance curve is not expected to have a significant impact on energy usage. For bypass factor, there will be zero bypass for all ductless systems, so we do not need to fit that performance curve.

Based on this data set, Solaris has developed a draft methodology for deriving a set of performance curves from product data, evaluating the goodness of fit, and also evaluating the suitability of using performance curves from one product to model another product. The outline for this process used for cooling mode:

1. For each product data sheet:
   1. Plot data trends and identify outliers
   2. Create a weights table to place importance on non-outliers and relevant range of operating conditions
   3. Perform regression for COOL-CAP-FT
   4. Perform regression for COOL-EIR-FT
   5. Perform regression for COOL-EIR-FPLR
   6. Check overall goodness of fit to data using energy proxy calculation
   7. Record fit parameters and goodness of fit
   8. Renormalize fit parameters for eQUEST reference temperatures
2. Compare performance curves across products using energy proxy calculation
3. Compare performance curves across products using eQUEST
4. Make choices about modeling measure offerings

After completing the analysis for cooling mode, we next implemented the same process for heating mode. That process is reasonably similar, but with slight modifications: we perform regression for HEAT-EIR-FT and HEAT-EIR-FPLR in a single step, and no “renormalization” step is required.

Here are the details for each step.

# 1a. Plot data trends and identify outliers.

From the raw data, we calculated the EIR and PLR values, and for a selected indoor/outdoor temperature condition, plotted trends against compressor speed. We observed for a number of models that the data point for “rated” speed appears to be an outlier from the other data points. In some cases, the “rated” speed produces the same cooling output as the “75%” speed, but with up to 20% lower power input. This shows up as an outlier in the plot of EIR vs PLR, with two values of EIR around one value of PLR. This scenario cannot be modeled without more information because it is not clear whether the system would meet the load by operating at “75%” or “rated”. Without detailed knowledge of the procedure used to develop these data tables, Solaris felt that the reasonable approach to handle this scenario was to develop a weighted least squares regression in the next step, and give a lower weight to the outliers in the data. The EIR value for 75% lines up with the trend for other speeds, but the EIR value for “rated” speed does not line up with the general trend. Hence, the “rated” speed was treated as an outlier in the later steps.



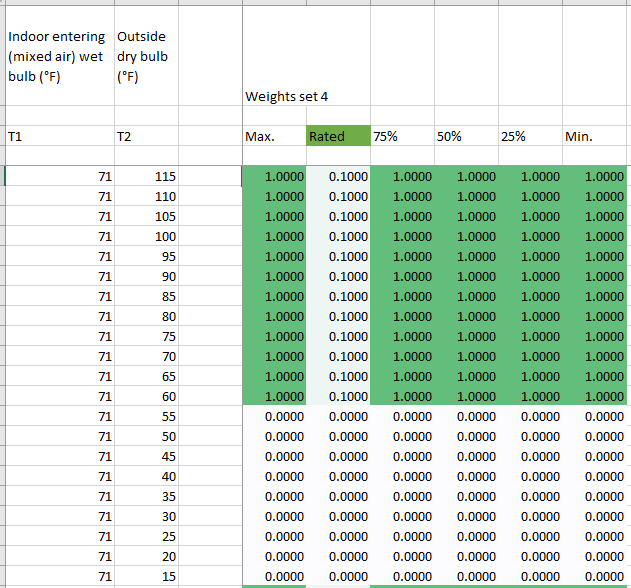
## Create weights

Since the performance curves will be used to model energy usage across the full range of data points (T1, T2, speed), as a general strategy we try to use all these data points in the regression. So, we created weights tables with the same shape to provide a regression weighting for each data point (T1, T2, speed). Then, each regression can be treated as a minimization problem seeking the least error sum of squares:

Error(T1, T2, speed) = weights(T1, T2, speed)\*curve-fit(T1, T2, speed) – weights(T1, T2, speed)\*data(T1, T2, speed)

Weighted error sum of squares = Sum over all T1, T2, speed: (error(T1, T2, speed))^2

Looking at the data sheet, we observed footnote for cooling mode, “It may not reach the above capacities in low ambient temperatures,” referring to outdoor dry bulb temperatures of 65 °F and below. So we gave low weights to these low temperatures, and low weights to the outlier speed (=”rated”). After trying several variations, we created a weight set labeled option 4, that was used for the draft set of performance curves. The weights are equal across different indoor wet bulb temperatures.



Note that performance curves from DEER 2020 prototypes came in three flavors for COOL-EIR-FPLR: “tem” (temperature), “mod” (moderate), and hot. Logic in the prototype triggers one flavor depending on climate zone.[[3]](#footnote-3) Although we don’t know the source of these curve fits, we can hypothesize that these three flavors may have been developed with different weights that give more priority to the low, medium, or high end of temperatures and/or PLRs. (An alternate possibility is that the team expected manufacturers to supply slightly different variations on the same SEER model depending on climate.) We propose that, this approach should be considered only if it is seems necessary for accurate modeling, depending on the goodness of fit and quality of eQUEST results. Essentially, that process would be to develop different multiple sets of performance curves, each prioritizing a different part region of the performance table to fit. For a given building simulation, we can use the hourly outputs from eQUEST to tabulate the hours that a given cooling system spends in each (T1, T2, PLR) bin, and use that for the weights. However, for this first draft we prefer to develop one set of performance curves, and see if that works.

# 1b. Perform regression for COOL-CAP-FT

Note that it was a choice to perform regression for one performance curve at a time, and in this sequence (CAP-FT first, then EIR-FT, then EIR-FPLR). This choice was supported by checking goodness of fit as will be discussed in a later section.

COOL-CAP-FT is used to describe the available (maximum) cooling capacity that the system can provide. At every hour of the simulation, eQUEST will calculate available capacity as COOLING-CAPACITY (nominal) \* COOL-CAP-FT(T1,T2). The available capacity is used to cap the output of the system, and also as the reference for PLR = 1. As a corollary, eQUEST will never request the system to evaluate performance curves with PLR>1.

For this regression, we need to select a reference speed. We will not use capacity data from other speeds during the regression for this curve. In the implementation, we have used “max” speed for the reference speed.

We also imposed a constraint on the curve fit that fixes COOL-CAP-FT = 1 at reference temperatures, as per eQUEST. In eQUEST the reference temperatures can input by the user, but the defaults (as used in DEER 2020) match the AHRI standard rating conditions, so when those conditions were available in the data we used 67 °F for the reference indoor wet bulb, and 95 °F for the reference outdoor dry bulb. For two products with 3 ton nominal cooling capacity, data were only available at 94 °F and 98 °F, so we used the 98 °F temperature for reference while fitting the curves, and later renormalized the coefficients and nominal value to work with eQUEST reference temperatures; see the section on renormalization.

In our workbook, for each product data sheet, there is a worksheet set up with the raw manufacturer data, plots of the raw data, a control panel for entering the curve-fit coefficients and starting regression calculations and measuring goodness of fit, plots of representing the goodness of fit, tables of values calculated from raw data, and tables of data calculated from the regression coefficients.

**To perform the regression for cool-cap-ft:** click the button next to the “cool-cap-ft error” cell. That pulls up the Excel solver add-in dialog, pre-filled with a range of cells to vary (regression coefficients), constraint cells (cool-cap-ft at reference temperature), and the error cell to minimize. The user has to click OK to start the solver, then OK again to accept the solver result. Before performing regression, the performance curve coefficients are arbitrary values.

At this draft stage, we used solver to run minimization, instead of entering formulas for the regression coefficients or using the regression add-in, because it allows the flexibility to quickly change the definition of error terms being minimized in order to research alternate regression methods. A disadvantage of using solver is that the result is not guaranteed to be unique, so solver might give different coefficients each time the user runs regression. If the method is deemed reasonable, we could switch this to hard-coded formulas or using the regression add-in. Meanwhile, as a way of keeping track of the regression result, we copy the regression coefficient values to a summary in the first worksheet (“Models”).

At this point, we check the goodness of fit for capacity. We can first consult the plot for a visual comparison of data and regression curves. Exact fit is not possible because lower temperature data does not follow a smooth, quadratic trend. Next, the cell labeled “COOL-CAP-FT error” shows a live calculation for the weighted error sum of squares just for this performance curve; a lower number means that the data can be fit with the biquadratic regression offered by eQUEST. From this data set and weights, a good fit will be around ~0.1, and a bad fit will be around ~0.2.

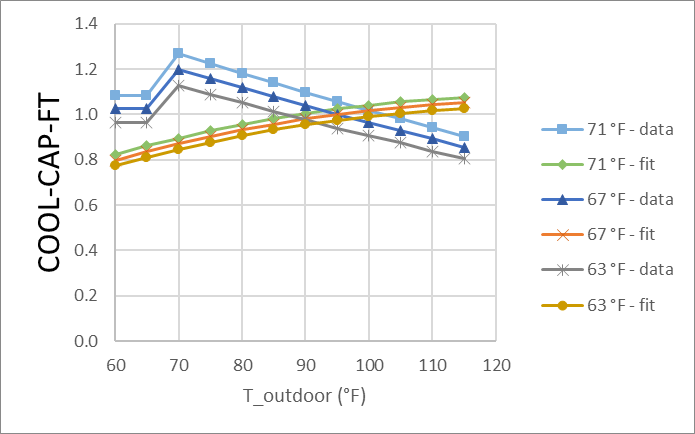


Figure . Poor fit for COOL-CAP-FT with arbitrary curve coefficients.

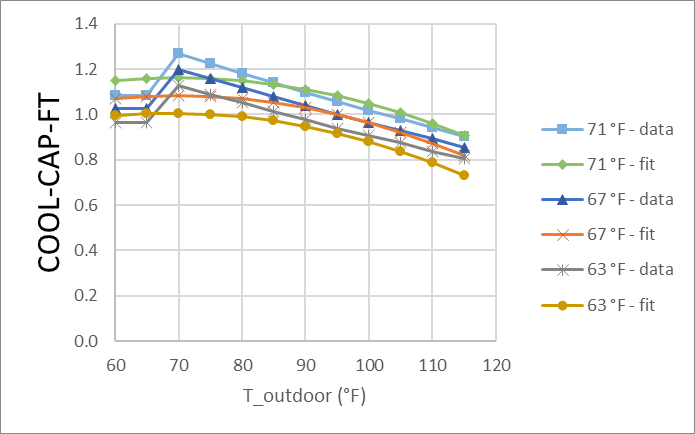


Figure . Better fit after performing regression.

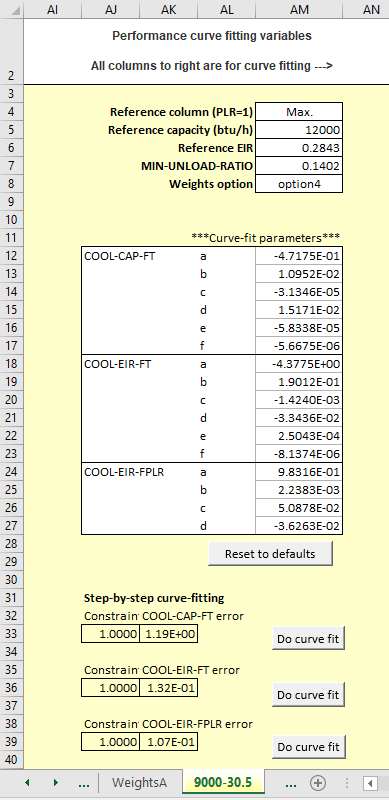


Figure . Regression control panel for the product with 9000 btu/h capacity at “rated” speed and 30.5 SEER.

# 1c. Perform regression for COOL-EIR-FT

The EIR curves (EIR-FT and EIR-FPLR) are used in eQUEST together, so the regression needs to be coordinated. In order to fit the EIR curves individually, the first step is to fill out a table for the actual performance data by calculating EIR and PLR for every provided data point (T1 = indoor wet bulb, T2 = outdoor dry bulb, and speed). We then break down the temperature and PLR components of EIR at every data point, so that EIR(T1,T2,PLR) = EIR(T1\_ref,T2\_ref,PLR=1) \* EIR-FT(T1,T2) \* EIR-FPLR(PLR) and EIR(T1\_ref,T2\_ref) = 1 and EIR-FPLR(PLR=1) = 1. To meet these requirements, we used these formulas:

PLR\_data = capacity\_data(T1,T2,speed) / capacity\_data(T1,T2,speed\_ref)

EIR-normalized\_data (T1,T2,PLR) = EIR\_data (T1,T2,PLR) / EIR\_data (T1\_ref,T2\_ref,PLR=1)

EIR-FPLR\_data (PLR) = EIR-normalized\_data (T1,T2,PLR) / EIR-normalized\_data (T1,T2,PLR=1)

EIR-FT\_data (T1,T2) = EIR-normalized\_data (T1,T2,PLR) / EIR-FPLR\_data (PLR)

In this setup, PLR=1 refers to the speed column selected as the reference column.

Next, we prepare for regression. In this first draft, we have set up cells with formulas that take the given curve-fit coefficients calculate the performance curve values corresponding to each data point (T1, T2, and speed), to be used with Solver to minimize the error between data and curve-fit for each performance curve. We arranged these cells into a table where (T1, T2) vary by row and speed varies across columns. For COOL-EIR-FT, the performance curve-fit is a function of (T1, T2) only, so the value depends only on row and not on column. A “COOL-EIR-FT error” cell calculates the weighted error sum of squares, comparing the COOL-EIR-FT from raw data and the COOL-EIR-FT performance curve with the given coefficients.

**To perform the regression for COOL-EIR-FT:** click the button next to the “COOL-EIR-FT error” cell and click through the solver dialogs. Then, check the goodness of fit by looking at the “COOL-EIR-FT error” value. For this data set, we found that we had good fit with values up to around 0.15, but poor fit with larger values. For a visual comparison, we plotted operating EIR (product of EIR at reference conditions, COOL-EIR-FT, and COOL-EIR-FPLR) for both the “max” and “rated” speeds. If “max” speed was selected as the reference speed, for goodness of fit, look at the “max” speed plot. We will check other goodness of fit information after completing the EIR-FPLR curve.

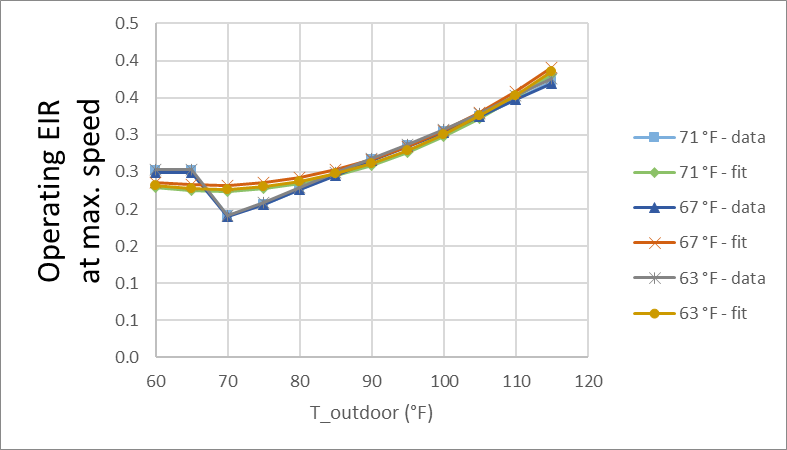


Figure . Visualizing EIR-FT goodness of fit by plotting operating EIR curve-fit and comparing to data, at the reference speed.

# 1d. Perform regression for COOL-EIR-FPLR

This step is similar to the previous steps. However, there is a distinction in that when we calculate EIR-FPLR component of EIR from raw data, it depends on EIR(T1, T2, speed). Hence, there may be variation with temperature (although at PLR=1, all rows take the value 1). So, since we want to fit this curve considering all possible (T1, T2) conditions, the error sum of squares for this regression includes the entire range of data for (T1, T2, speed), not only the row for the reference temperatures. This is why we need a weights table that includes all (T1, T2, speed) combinations.

Note one important caveat. Since PLR = output capacity / available capacity, when eQUEST calculates PLR for a given (T1, T2, load) condition, it must first calculate available capacity from the COOL-CAP-FT performance curve. So, in our regression calculator, to calculate the value of COOL-EIR-FPLR given curve-fit coefficients consistent with its interpretation by eQUEST, we first calculate a PLR value based on the cooling output from data divided by the “available capacity” as determined by the COOL-CAP-FT curve-fit coefficients. Thus, at any given (T1, T2, speed) data point, the PLR values may differ between manufacturer data and curve-fit calculations.

**To perform the regression for COOL-EIR-FPLR:** click the button next to the “COOL-EIR-FPLR error” cell and click through the solver dialogs. Then, check the goodness of fit by looking at the “COOL-EIR-FPLR error” cell. For this data set we had good fits with values up to around 0.15, and poor fit when error was larger. At this point, the operating EIR that eQUEST will calculate is completely determined (excluding cycling mode below MIN-UNLOAD-RATIO). So we can review the plots for operating EIR at a non-reference speed; COOL-EIR-FPLR as a function of PLR; and a scatter plot of operating EIR from performance curves vs operating EIR directly from product data. The last plot is probably most informative, as it shows very clearly either a strong correlation (close to the line y=x) or poor correlation. The scatter plot is not doing any filtering but plots all data points included those with zero weight in the error sum, so be advised to ignore the cluster of values all at one x-value (projected data for low outdoor temperatures). From this plot, we typically see that the products in this data set have good correlation at all speeds except “rated”, which departs from the line y=x when we have used “max” speed as reference for capacity and PLR=1. This also shows up on the plot of operating EIR as a function of temperature, and “rated” speed.

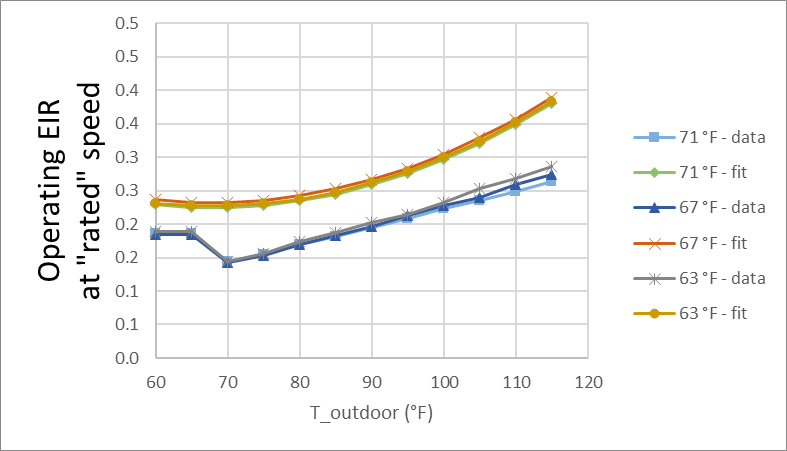


Figure . Operating EIR at speed with outlier data. Despite good fit for other speeds, performance curves are not expected to line up to data at this speed.

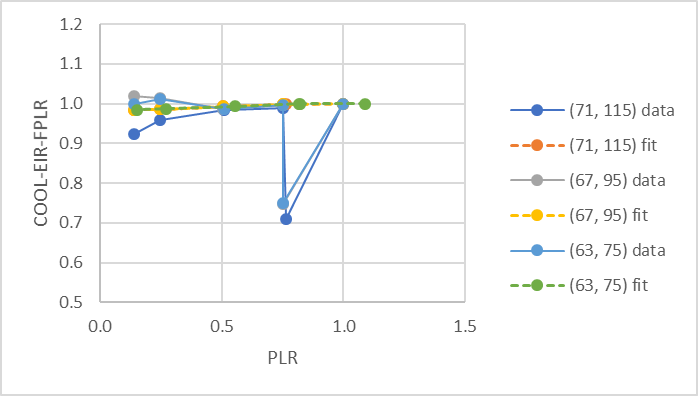


Figure . COOL-EIR-FPLR as a function of PLR, overlaying several temperature conditions. Data varies with temperature, but performance curve does not. The performance curve fits the average trend from data excepting data outliers, which have been given low weights. The PLR values may also differ between data and curve-fits.

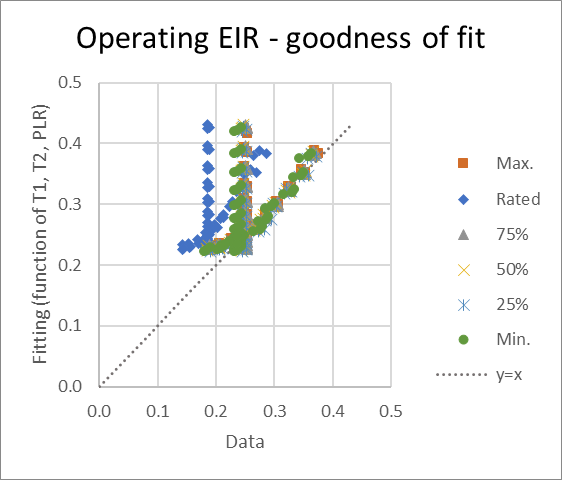


Figure . Goodness of fit compares data (x-axis) to performance curves with the given coefficients (y-axis). Rated speed data (blue) are all outliers, as are data points from low temperatures.

# 1e. Check overall goodness of fit to data using energy proxy calculation

Since the performance curves are all used together to calculate cooling energy usage in a given hour, we also want to see how well the performance curves fit the data in terms of energy. We created an energy proxy calculation:

We use our weights set as a stand-in for hours. For values from manufacturer data, all the terms on the right side can be calculated from the (T1, T2, speed) raw data. For the values from performance curves, we use the raw data for cooling output (btu/h) to calculate PLR. We can then make a scatter plot comparing energy proxy values from data to values from performance curves, and calculate the correlation coefficient (R^2).

The plots below show a reasonably good fit with R^2 = 0.996, then a poor fit with R^2 = 0.978. Most products with 9 kBtu/h and 18 kBtu/h had a good fit similar to this first plot. However, two products with 36 kBtu/h cooling capacity had poor fits. The poor fit is the best regression fit possible, but signifies that the calculation setup offered by eQUEST/DOE2 cannot perfectly match the whole range of performance data, depending on the product. By eyeballing the points far from the line y=x, we can guess that for some conditions, the eQUEST/DOE2 model using these poor fit performance curves will overpredict energy usage by roughly as much as 80%, and at other conditions underpredict by as much as 25%.

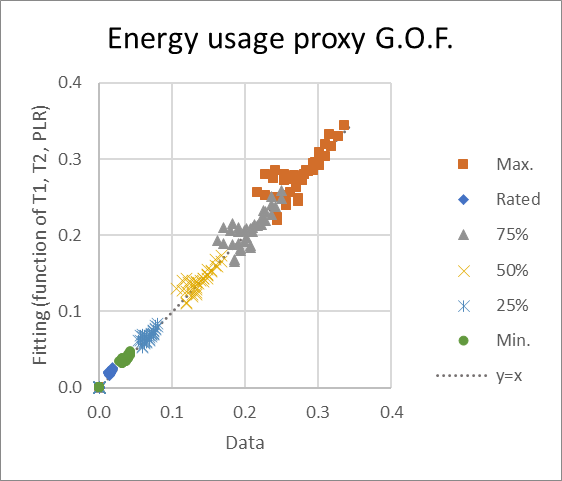


Figure . Overall goodness of fit for all three performance curves can be characterized by plotting the energy usage proxy value from using the performance curves (y-axis) against the value based on raw data (x-axis) at the same conditions for (T1, T2, cooling output). This plot shows good correlation (points all close to y=x), with R^2 = 0.996.

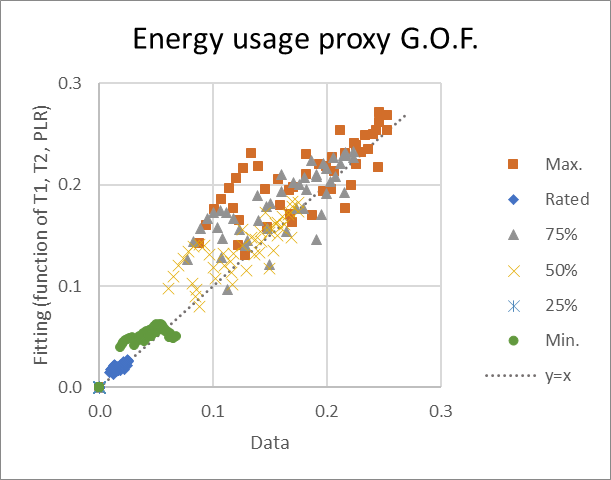


Figure . Overall goodness of fit using energy usage proxy value. This plot shows relatively poor correlation (many points away from y=x), with R^2 = 0.978.

Similarly, we can also look at how well the curves might predict total annual energy usage, using the same energy proxy calculation but adding up all (T1, T2, speed) data points instead of plotting. After we add up the total energy proxy calculation from all data points, we compute the error between data and performance curves. For the first plot above, the total energy proxy (normalized) was 26.6 calculated from raw data, and the performance curves overpredicted total energy proxy by 0.59 (2.2%). For the second plot above, the total energy proxy (normalized) was 25.6 calculated from raw data, and the performance curves overpredicted total energy proxy by about 3.3 (13%). The smaller prediction error for total “annual” energy (2.2% compared to 13%) was delivered by the performance curves with better correlation across all conditions. Of course, this depends on the weights. The annual energy usage error predicted by the eQUEST model will similarly depend on how much time is spent at (T1, T2, load) conditions where the performance curves underpredict and overpredict the data.

# 1f. Record fit parameters and goodness of fit

In this draft workbook, for each product, we used the product worksheet like a calculator to research the best options for fitting performance curves. So, the coefficients in each worksheet are not a “final” result. Instead, we copy the coefficients to a summary table in the first sheet (“Models”) along with other relevant values to record, such as speed used for reference, corresponding nominal capacity and EIR, min-unload-ratio, weight set used for weighted regression, error and correlation terms for judging goodness of fit. From this summary table we can highlight the columns we prefer for the “final” set of performance curves, and restore the “final” set of performance curves by copying back to the performance curve control panel in the individual product sheet: reference speed column, weights option, and regression coefficients.

# 1g. Renormalize fit parameters for eQUEST reference temperatures

In some cases we used the “max” speed rather than “rated” speed to create the available capacity trend as a function of temperature (also where PLR=1). Also, for a couple of products, we didn’t have performance data trends for the standard reference temperature conditions (T1 = 71 °F, T2 = °F), so we had to use slightly different reference temperatures for the curve fitting process. To address possible concerns arising from these scenarios, we created a worksheet that is a calculator allowing the user to input the original curve fit information, then set new reference temperatures (where COOL-CAP-FT = 1 and COOL-EIR-FT = 1) and new nominal capacity (at those reference temperatures). The sheet will calculate new “renormalized” performance curve coefficients (as well as new nominal EIR and min-unload-ratio) so that the operating EIR will exactly match the original performance curves at every (T1, T2, load) condition. (This refers to the full calculation for EIR, not normalized by the reference value.)

For reference, here are some equations that are used to renormalize the coefficients:

Change of reference temperature:

where (x,y) = indoor/outdoor temperature, Z = capacity or EIR, Z\_0 = reference value at old reference temperature, Z\_0’ = value at new reference temperatures, (a,b,c,d,e,f) = old coefficients, (a’,b’,c’,d’,e’,f’) = new coefficients. Function of PLR coefficients and min-unload-ratio are unchanged.

Rescaling nominal capacity:

Function of temperature curves are unchanged. Only update nominal EIR and EIR-FPLR curve, and min-unload-ratio.

Where x = PLR, Z = operating EIR, Z0 = nominal EIR, Z1 = COOL-EIR-FT, and primed values are for the new values after rescaling capacity. To hold cooling output constant, x \* nominal capacity (old) = x’ \* nominal capacity (new).

Note that available capacity and PLR are intermediate steps in calculating EIR, and without capping PLR at 1, the product (capacity\*PLR) will also exactly match between the original and “renormalized” performance curves, and thus energy will match as well. However, in eQUEST, if the user adjusts nominal capacity, there will be a difference in energy usage since eQUEST caps cooling output to available capacity (PLR = 1). Rescaling the nominal capacity could be used if the “max” speed was used to perform regression, but it physically makes sense to cap cooling output to “rated” speed. We should ask the manufacturer to comment on controls and whether “rated” output is the same as available capacity.

# 2. Compare performance curves across products using energy proxy calculation

We may want to ask: how similar are the performance curves for two different products? To answer this question, we set up a range of conditions for temperature and load/nominal, and computed the weighted energy proxy calculation for all the performance curves recorded in the summary tab. For pairs of candidates (model 1, model 2), we drew a scatter plot of the energy proxy calculation for: (model 1 on the x-axis, model 2 on the y-axis).

With these plots, we observed strong correlation / good agreement between the eight products at 9000 btu/h and 18000 btu/h nominal cooling capacity, across different SEER values. For convenience, it might be reasonable to use one set of performance curves to model all such pieces of equipment in eQUEST. However, note that we should also consider that the min-unload-ratio might be distinct across these products.

However, we also observed weak correlation / poor agreement between the two products at 36,000 btu/h nominal cooling capacity and each other, as well weak correlation between these and the lower capacity products. (Note that the goodness of fit to data was poor for the 36,000 btu/h, 20 SEER product.) Based on these observations, we might want to model the 36,000 btu/h products separately for each SEER rating, or try to gather additional product data.

We also included performance curves from DEER 2020 prototypes, for the user to research how the new performance curves compare. We did not plot the individual performance curves (COOL-CAP-FT, COOL-EIR-FT, and COOL-EIR-FPLR)

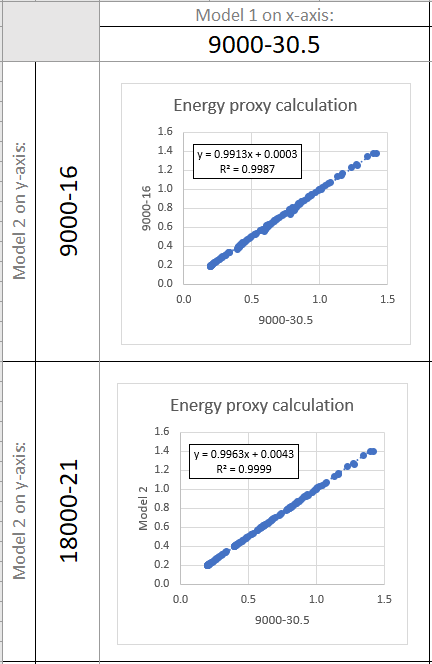


Figure . Comparing model 1 (9,000 btu/h & 30.5 SEER) to model 2. At top, model 2 = (9,000 btu/h & 16 SEER). At bottom, model 2 = (18,000 btu/h & 21 SEER). Both comparisons show strong correlation.

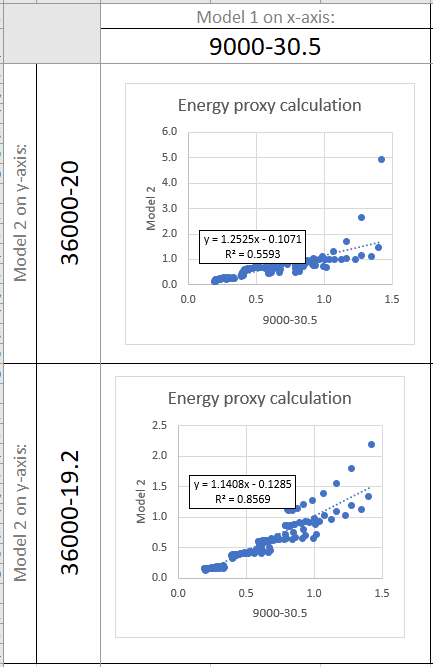


Figure . Comparing model 1 (9,000 btu/h & 30.5 SEER) to model 2. At top, model 2 = (36,000 btu/h & 20 SEER). At bottom, model 2 = (36,000 btu/h & 19.2 SEER). Both comparisons show weak correlation (slope is far from 1.0, R^2 less than 0.99).

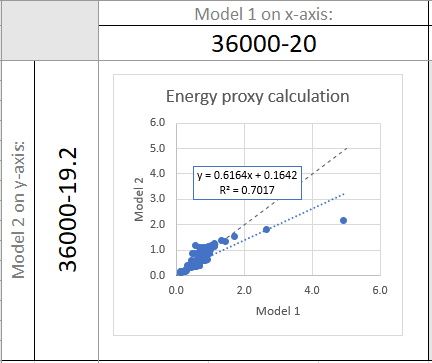
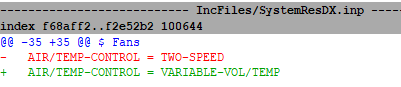
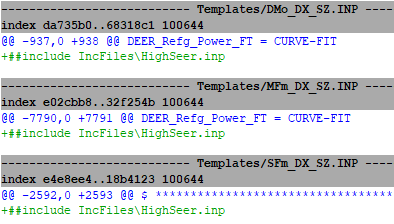


Figure . Comparing performance curves from model 1 = (36,000 btu/h & 20 SEER) to model 2 = (36,000 btu/h & 19.2 SEER). The comparison shows weak correlation, even though both models are close in capacity and SEER rating.

# 3. Compare performance curves across products using eQUEST

## Setup

To implement the model in eQUEST via MASControl3, we made the following changes:

* Start with prototypes and techIDs as modified for SWHC050-01: Ductless mini-split heat pump.
* SYSTEM:AIR/TEMP-CONTROL: change from TWO-SPEED to VARIABLE-VOL/TEMP. In DEER 2020 residential prototypes, this keyword value is hard-coded in SystemResDX.inp.  
  
* Create a new file (IncFiles/HighSeer.inp) to hold the new performance curves; use #include command to reference this file in each residential prototype.  
  
* In the MC3 tech workbook most closely related to the measure equipment (TechData\_PkgHVAC.xlsm), copy the techID for SEER 15 ductless heat pump as used in the SWHC050-01 workpaper (MiniHP1Sp-E11.7-S15.0-H8.7). Create one new techID (e.g. TechID = curve\_BTUH9000\_SEER30.5) for each product from which new performance curves were developed; let’s call this block 1 of test runs. Update the MC3 parameters being passed to prototypes:
  + NumStages = 2 (triggers LowSpdCapRatio parameter)
  + LowSpdCapRatio, e.g. 0.187 (sets MIN-UNLOAD-RATIO keyword)
  + ClCap\_fT, e.g. BTUH9000\_SEER30.5\_CAP\_FT (sets COOL-CAP-FT keyword)
  + EIR\_fT, e.g. BTUH9000\_SEER30.5\_EIR\_FT (sets COOL-EIR-FT keyword)
  + CEIR\_fPLR\_Tem, CEIR\_fPLR\_Mod, and CEIR\_fPLR\_Hot: assign same value, e.g. BTUH9000\_SEER30.5\_EIR\_FPLR (sets COOL-EIR-FPLR keyword)
  + For this block of test runs, keep parameter EER constant between runs (used to calculate CoolingEIR parameter, which in turn is used to set COOLING-EIR keyword).
* Copy block 1 to make block 2 of test runs with the following modifications (e.g. TechID = full\_BTUH9000\_SEER30.5):
  + SEER = nominal SEER from product, e.g. 30.5 (ignored in prototypes)
  + EER = 0.99 (not part of data set, ignored)
  + CoolingEIR = nominal EIR corresponding to performance curves, e.g. 0.28433 (sets COOLING-EIR keyword)

I used MASControl3 to run these new TechIDs through the simulation engine, DOE2, with filters BldgHVAC = rDXHP, BldgType = SFm, BldgVint = 2007, T-stat = T3. Simulation notes:

* In the first run of simulations, all tech runs for CZ16 failed in simulation after “Starting HVAC” in the simulation log file. We expect the INP file needs to be debugged by opening in eQUEST to identify other potential sources of error.

## Results – block 1

Here is a scatter plot comparing the baseline techID (MiniHP1Sp-E11.7-S15.0-H8.7 from SWHC050-01) to each new techID from block 1, in which only the performance curves are updated. The nominal EIR is constant across all techIDs.

Looking at the results by climate zone, we can see that in a number of climate zones, the new performance curves give decreased annual cooling energy compared to the baseline model (CZ02, CZ04, CZ10, CZ11, CZ12, CZ13, CZ14, CZ15). In a handful of climate zones, the new performance curves give slightly increased annual cooling energy compared to the baseline model (CZ06, CZ07, CZ08). In other climate zones, changes are negligible (CZ01, CZ03, CZ05, CZ09). The results for CZ16 are incomplete due to simulation errors.

## Results – block 2

Here is a scatter plot comparing the baseline techID (MiniHP1Sp-E11.7-S15.0-H8.7 from SWHC050-01) to each new techID from block 2, in which both the performance curves AND the nominal EIR are updated from the new analysis of product data.

Looking at the results in any given climate zone, the usage trend is hard to describe. We would hope to find the following trends:

* Within product series for 9,000 btu/h, usage increases with decreasing SEER. This trend seems to hold true.
* Within product series for 18,000 btu/h, usage should increase with decreasing SEER. This trend holds true with the exception of the SEER 20.5 model, which shows lower usage than SEER 21 in every climate zone.
* Within product series for 36,000 btu/h: note that the performance curves for the second to last model (36,000 btu/h, SEER 20) were a poor fit to data, so we should assume the results for this simulation are incorrect.
* Across product series: We would expect to be able to match up SEER 16 and SEER 18 models across the 9,000 btu/h series and 18,000 btu/h series. However, at the same SEER, the 18,000 btu/h models use more energy. Note that in the simulation, all systems have the same capacity. So, there is a substantial range in the nominal EIR ratings from different products at the same SEER. This range is present in the source data, and not an artefact of simulation setup. This suggests that we should have a larger number of products to be able to identify an “industry average” value for any given SEER rating.

# 4. Make choices about modeling measure offerings

In an ideal world, we would love to have multiple data sheets matching up exactly to each measure offering (e.g. SEER 19), and thus be able to simulate multiple pieces of equipment and take the average savings. However, what we have is a sparse set of product data for off-design performance, and evident differences in performance at the 36,000 btu/h capacity range compared to the 9,000 btu/h – 18,000 btu/h range. So, we have to extrapolate and apply the performance curves from products we do have, to the measure offerings. Below is an arbitrary assignment for performance curves.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Offering description** | | | **Simulation details** | | |
| Technology | Cooling Capacity Range | SEER Rating | EIR | HIR | Performance curves |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | <36,000 BTUH | 19 (<20) | 0.29543 | 0.33375 | BTUH9000\_SEER30.5 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | <36,000 BTUH | 20 (<21) | 0.27580 | 0.32347 | BTUH9000\_SEER30.5 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | <36,000 BTUH | 21 (<22) | 0.26781 | 0.32194 | BTUH9000\_SEER30.5 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | <36,000 BTUH | 22 (<23) | 0.26553 | 0.31752 | BTUH9000\_SEER30.5 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | <36,000 BTUH | >=23 | 0.24106 | 0.29381 | BTUH9000\_SEER30.5 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | >=36,000 BTUH | 19 (<20) | 0.29671 | 0.33134 | BTUH3600\_SEER21 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | >=36,000 BTUH | 20 (<21) | 0.28441 | 0.31617 | BTUH3600\_SEER21 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | >=36,000 BTUH | 21 (<22) | 0.28463 | 0.32472 | BTUH3600\_SEER21 |
| Variable Speed Ductless Heat Pump (Mini-Split or Multi-Split) | >=36,000 BTUH | >=22 | 0.27537 | 0.32040 | BTUH3600\_SEER21 |

# References

(1) ahri data res minisplit HP 2020-06.xlsx [5.50 MB]

(2) SCE HVAC Data-AE+NF 2020-10-16.xlsb [3.32 MB]

(3) HighSeer.inp [plaintext]

1. “ahri data res minisplit HP 2020-06.xlsx” [↑](#footnote-ref-1)
2. The non-temperature variable is not labeled in the data but simply shows as “Max … Rated … 75% … 50% … 25% … Min”. Solaris called Mitsubishi to request clarification, and it was explained to represent a compressor loading or compressor speed variable. We note that this is not the same as eQUEST’s part load ratio. [↑](#footnote-ref-2)
3. From the Parameters table for ParamID = CZ\_Category: CZ1, CZ3, CZ5-CZ7, and CZ16 are temperate; CZ2, CZ4, CZ8-CZ10, CZ12, and CZ13 are moderate; and CZ11, CZ14, and CZ15 are hot. An older set of data from the DEER\_fClimate table had CZ1, CZ3-CZ8 and CZ16 as temperate; CZ2, CZ9, CZ10, CZ12, and CZ13 as moderate; and CZ11, CZ14, and CZ15 as hot, but these older categories are unused in DEER 2020. [↑](#footnote-ref-3)