Pathian Incorporated

Generating, cataloging and applying global energy efficiency performance standards

– Daniel Buchanan, Founder and President of Pathian Incorporated

Abstract:

In 2010, Pathian Incorporated filed and received a U.S. patent for a new energy benchmarking method called Pathian® Analysis. This benchmarking process is fundamentally different from all other benchmarking processes that have come before it. The inventor identified the time period of evaluation, *not weather*, as the principle barrier to accurately compare a user's energy consumption habits. This paper explains the rationale behind this new benchmarking process, the distinct advantages it has over nationally accepted weather-normalization methods, and how it can be applied to improve traditional benchmarking processes for both buildings and HVAC equipment.

Overview:

This paper shall first introduce the reader to Pathian® Curves, discuss the difference between Pathian Curves and traditional baseline comparison energy curves, and show how these weather-normalized energy curves are used to create performance indices in order to analyze peer group performance for commercial buildings, mechanical systems and their components. Once the reader has a basic understanding of Pathian Curves, we will introduce the Syrx™ Numbering System, a peer group classification system used to catalog performance indices for peer comparison. We will then show how these curves and performance indices can be used to create the first catalog of national performance standards for all energy-consuming devices affected by weather.

The reader will be introduced to five new types of energy benchmarking methods made possible by this new analysis technique called Pathian Analysis: Group Benchmarking™; Peer Benchmarking™; Position Benchmarking™; Control Sequence Benchmarking™; and Load to Position Benchmarking™. As a practical application, it will show how performance indices and these benchmarking methods can be used to conduct automated energy audits and real-time fault detection of HVAC mechanical systems. At the conclusion, the reader shall understand how utilization of Pathian Analysis can reduce instances for inefficient operation of HVAC mechanical systems by effectively using information currently available through the building's existing direct digital control (DDC) systems. Using Pathian Analysis, weather normalization is simplified, allowing more accurate peer comparison of building HVAC systems which shall support more cost-effective identification, quantification and sustainment of energy conservation projects for the building owner/operator and the HVAC industry.

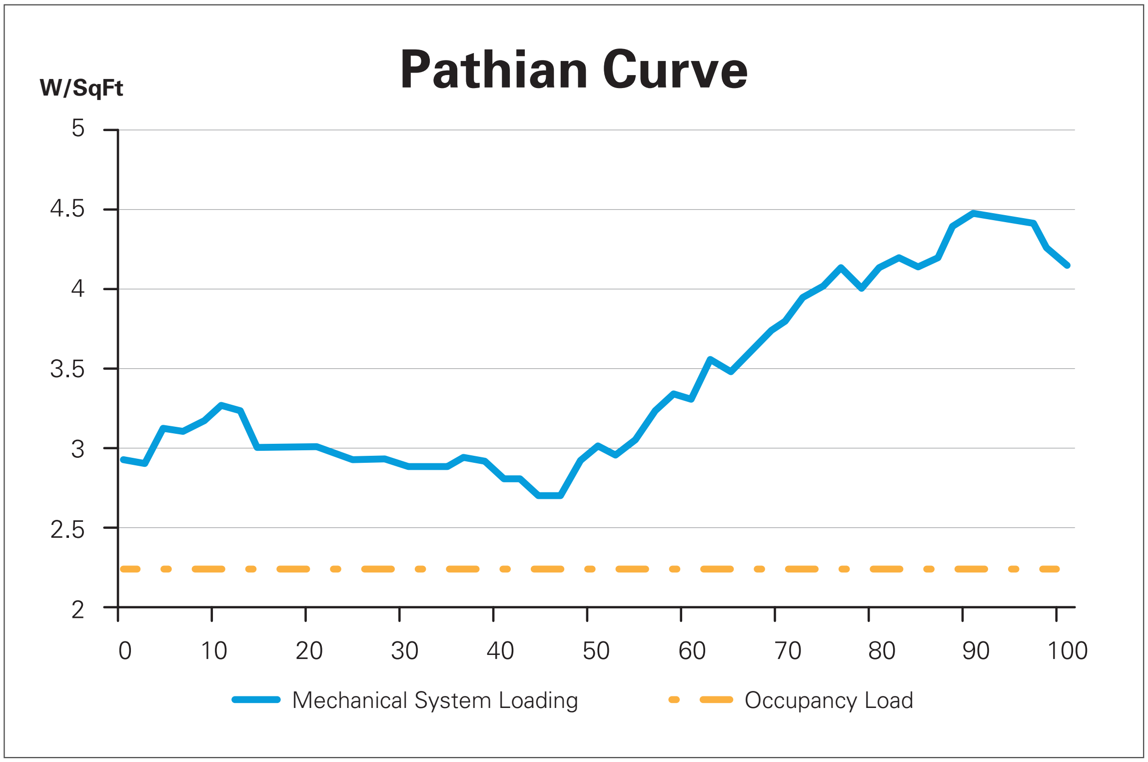


Figure 1: Pathian Curve (U.S. Patent No. 8,719,184)

Discussion:

In general, the energy industry is very good at measuring the energy consumption habits of commercial buildings. An excellent example of this is utility company billing. For decades, companies have produced accurate billings for their customers. Comparing how peer energy systems consume energy, however, has proven a much more difficult task. Differences in weather conditions have long been considered the primary source of these difficulties. In 2008, Pathian began developing a new HVAC control system commissioning software application. The purpose of the application was to quantify energy savings derived from modifications of an HVAC's DDC system algorithms. To achieve this goal, Pathian revisited the process of how differences in weather conditions were analyzed in the benchmarking process. Pathian concluded that differences in weather conditions were not the problem in energy benchmarking. Instead, Pathian identified the time period of analysis as the principle barrier to accurately comparing our energy consumption habits.

Pathian's approach was simple: the smaller the time period, the less effect the differences in weather conditions had on the benchmarking process. If the time period was held very small (e.g., 15-minute interval or less), then weather could essentially be treated as a constant in the energy benchmarking calculations. Using this approach, the question asked was simply how much energy was consumed during a very small time period at a very specific outside air condition. The resultant energy curve is shown in Figure 1. Pathian called this new benchmarking process Pathian Analysis and the energy curve it generated was named a Pathian Curve (U.S. Patent No. 8,719,184).

To explain how Pathian's benchmarking process compares to other methods, three (3) baseline energy curve examples are shown. Each energy curve was generated from the same 15-minute interval data. This information was gathered from the primary electric meter data of a large commercial building over a one-year period. The first two examples evaluate energy consumption by using contemporary measurement and verification protocols. In the third example, the baseline curve was generated using the Pathian Analysis technique.

Example #1:

The energy curve shown in Figure 2 is a typical scatter chart plotting energy demand (kW) vs. time (months). Using Microsoft Excel®, a typical best fit energy curve has been added to the chart. The result is a sixth-degree polynomial that describes how the system consumed energy over the one-year period. This best fit energy curve is **location** and **time** period specific. More significantly, it is strictly bound to the weather conditions that occurred during the year it was created.

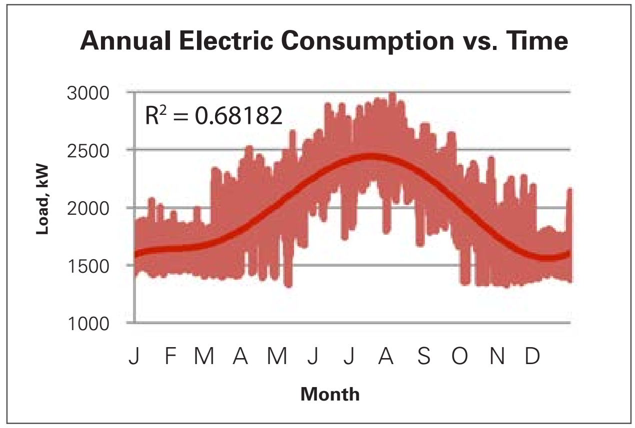


Figure 2: Calendar year base energy curve

In order to compare this curve to another time period, adjustments for differences in weather conditions that occurred between the two periods must be made. This weather normalization process can have a significant impact on the economics of the energy measurement and verification process. The greater the accuracy required, the greater the cost of the measurement process.

Example #2:

In Figure 3, the energy curve references the same data set but plots it in a different way. In this case, energy demand (kW) vs. temperatures that occurred over the one-year period of evaluation is plotted in 15-minunte time intervals. Again, a best fit energy curve has been added to the chart. Plotting data with this approach normalizes the building load data to weather conditions, eliminating the location and time period components from the analysis. Therefore, data for this curve can be directly compared to another similar energy curve without any further weather normalization methods being applied. The fundamental problem with this energy curve, however, isn't weather conditions; it is accuracy. The best fit polynomial smoothes out all the details of how the energy system actually consumed energy between one temperature and another.

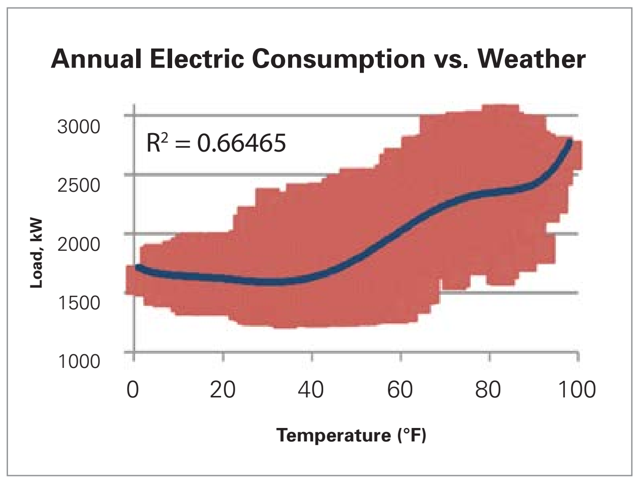


Figure 3: Traditional weather-based energy curve

Example #3:

In this example, a Pathian Curve builds upon the same 15-minute interval energy consumption data collected in Example #2. The first step in the process is to assign a weather stamp (e.g., temperature, enthalpy, etc.) to each interval building load record in the data set. This ties energy consumption to a specific weather condition for the time period analyzed. Next, the interval data is sorted into very small bins associated with the chosen weather condition. In this example, temperature bins are established in 1 °F increments. The first temperature bin is created at 0 °F, which represents the lowest temperature that occurred for the data set during the time period of evaluation. Additional bins at each interval temperature are created until the highest temperature is reached that occurred in the data set (98 °F). The result is the creation of 98 separate temperature bins for the data set. An example of the temperature bin sorting can be seen in Figure 4.

For each temperature bin, we then use an averaging technique to quantify the energy consumption within each temperature bin. The calculated values are precise bin average values (BAV) that perfectly describe the average performance of the energy system at each interval weather condition. This process is shown in Figure 5. To allow more detail, only the range of bin temperatures between 40–45 °F is shown. A Pathian Curve is then generated from the bin average values to create an n^{th} degree polynomial, where n is the number of horizontal subdivisions. The resulting Pathian Curve is shown in Figure 6. In this example, the curve's appearance resembles a 98^{th} degree polynomial that precisely depicts how the enegy system comsumed energy during the period of evaluation.

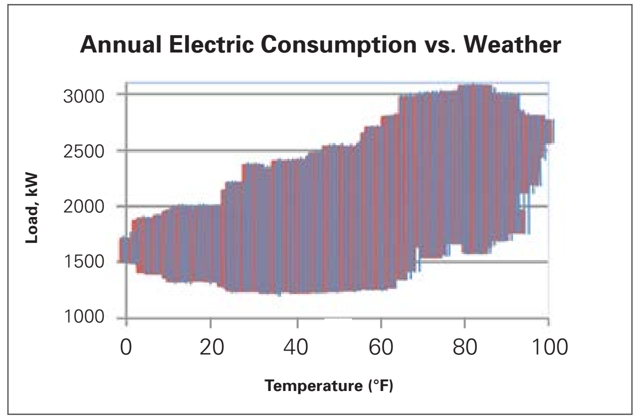


Figure 4: Vertical data sorting over interval temperatures

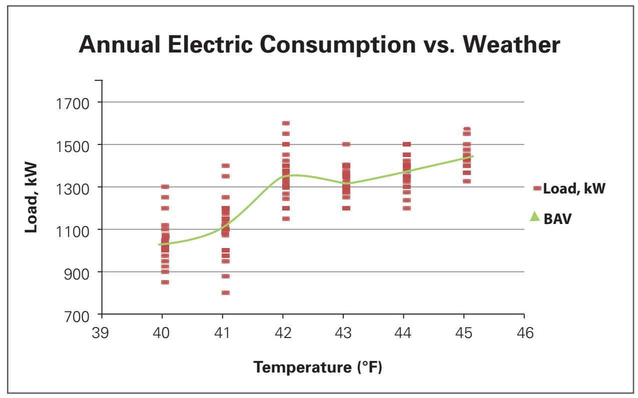


Figure 5: A precise benchmark is calculated at each interval temperature

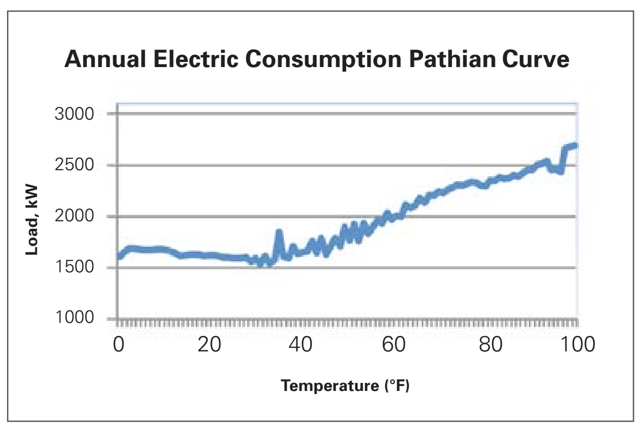


Figure 6: A Pathian Curve is generated from many interval BAVs

Accuracy of Pathian Baseline Curves Compared to Traditional Methods

The American Society of Heating, Refrigeration, Air Conditioning Engineering (ASHRAE) and International Performance Measurement and Verification Protocol (IPMVP™) publish guidelines for the HVAC industry on how to measure energy curve accuracies. While a complete discussion on these methods is beyond this paper's scope, it is important to review a key statistical concept called the **coefficient of determination**. The coefficient of determination is denoted as R^2 or r^2 and pronounced "R squared". In the context of energy measurement and verification, the R^2 value is a number between zero (0.00) and one (1.00) that describes how accurately the data used for the best fit polynomial curve represents the data set from which it was generated. Generally speaking, a value of 0.00 means that there is no correlation between the energy curve and the data set. A value of 1.00 means there is a perfect correlation between the energy curve and the data set. The U.S. federal government requires R^2 value of at least 0.70 to process payment applications for energy conservation projects (using Whole Building Approach — Method C as outlined in FEMP M&V Guidelines: Measurement and Verification for Federal Energy Projects).

Establishing an accurate baseline is very important. Errors in the baseline will propagate throughout the entire measurement and verification process, making final results less accurate and actionable. Referring to our first two baseline curve examples, the coefficient of determination (R^2) value of Examples #1 and #2 equals 0.6818 and 0.6646, respectively. Based on these R^2 values, the energy curve of Example #1 is slightly more accurate describing the data set than Example #2. Neither curve's R^2 value, however, is greater than 0.70, which means they could not be used for measurement and verification purposes for federal government energy conservation work. In contrast, the Pathian Analysis process consistently generates an R^2 of nearly 1.00 for every energy curve because the benchmarking process retains the details of how the energy was actually consumed.

Using Pathian Curves to Calculate Energy Consumption

A Pathian Curve describes the average performance of an energy system or component across selected weather bins. To calculate the energy consumption for a specific weather bin, the count of energy records for each individual weather bin (i.e., bin count) is simply multiplied by the calculated bin average value (BAV), as shown in Equation 1:

$$E_1 = (BAV_1) * (BC_1) \quad (1)$$

Where: E_1 = Weather Bin Energy Consumption
BAV_1 = Bin Average Value
BC_1 = Bin Count

For example, if there were 100 hourly readings at a particular weather bin and the BAV for that weather bin was 100 kW, the total energy consumption for that period would be 100 kW *100 hours = 10,000 kWh. This is not an approximated value. It represents the precise energy consumption for that particular weather bin. Thus, if this process is repeated for each individual weather bin and the results are summed, the exact energy consumption for that period is precisely calculated with a very high degree of accuracy by using Equation 2:

$$E_{total} = (BAV_1 * BC_1) + BAV_2 * BC_2 + \ldots\ BAV_n * BC_n \quad (2)$$

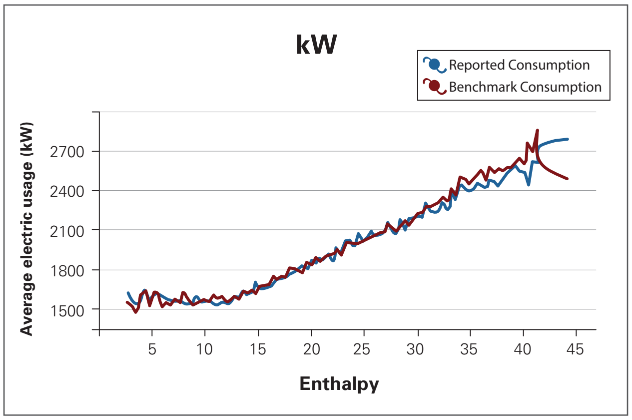


Figure 7: Pathian Analysis comparison chart

In Figure 7, two Pathian Curves are shown. The red curve is the benchmark year, and the blue curve is called the comparison curve. In this example, the comparison curve represents the following year, but it could be any year of our choosing. Within this two-year span there were no major changes to building systems or how they were controlled. As a result, notice how similar the BAVs are at each interval weather condition. This is expected if the customer's energy consumption habits have not changed during the time period of evaluation. In Figure 8, a difference curve generated from the same data set is shown. The function of the difference curve is to graphically illustrate the calculated "difference" between the benchmark year BAV and the comparison year BAV at each temperature bin, helping to pinpoint specific areas of focus and improvement. For example, in Figure 8, the larger difference between the benchmark year and comparison for enthalpy values above 30 Btu/lb shows that more significant efficiency improvements occurred during cooling season.

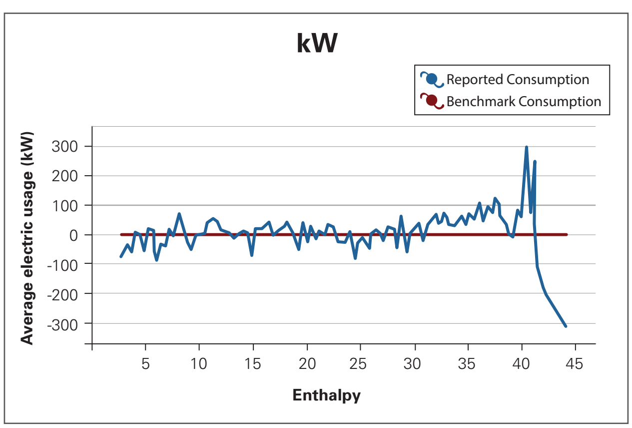


Figure 8: Pathian Analysis difference curve

Using Pathian Curves to Calculate Weather-Normalized Variances in Energy Consumption

Calculation of weather-normalized energy consumption variances is achieved by comparing Pathian Curve BAVs between one time period and another. Interval data for the selected baseline time period is used to generate a Benchmark Curve by plotting calculated baseline year BAVs for each weather bin. Similarly, interval data for the selected report year is used to generate a Comparison Curve. The BAV difference between the Benchmark Curve and the Comparison Curve is calculated for each individual weather bin benchmark value and then multiplied by the weather bin hour count from Comparison Curve time period, as expressed in Equation 3:

(3) $E_{diff1} = (BAV_{BY1} - BAV_{CY1}) * BC_{CY1})$

Where: E_{diff1} = Difference in Energy Consumption for Weather Bin

BAV_{BY1} = Benchmark Curve Weather BAV

BAV_{CY1} = Comparison Curve Weather BAV

BC_{CY1} = Comparison Curve Bin Count

For example, at 40 °F if the Benchmark Curve's weather BAV is 100 kW and the Comparison Curve's corresponding weather BAV is 90 kW, then the average difference in electric demand at 40 °F is 10 kW. For the report year, if 100 hours were spent within that particular weather bin (40 °F), the total difference would be (100 kW – 90 kW) X 100 hours = 1,000 kWh for that weather bin. If this process is repeated for each individual weather bin and results are summed, the weather-normalized energy consumption difference between the two time periods is precisely calculated. This process is represented in Equation 4 below:

(4) Annual Energy Consumption Difference = $(BAV_{BY1} - BAV_{CY1}) * BC_{CY1}) + (BAV_{BY2} - BAV_{CY2}) * BC_{CY2} + \ldots. (BAV\ldots_{BYn} - BAV\ldots_{CYn}) * BC\ldots_{CYn})$

where: $BAV_{BY1,2.n}$ = Bin Average Value for Benchmark Year at Specific Weather Bin

$BAV_{CY1,2.n}$ = Bin Average Value for Comparison Year at Specific Weather Bin

$BC_{CY1,2.n}$ = Bin Count for Comparison Year at Specific Weather Bin

This process is shown graphically in Figure 9 where Pathian Curves have been plotted for both the benchmark and comparison years. In this example, the commercial building had performed extensive energy conservation measures over five years. The red curve is the Benchmark Curve that represents how the facility consumed electricity in the baseline year. The blue curve is the Comparison Curve, representing how the building consumed electricity five years later after implementing identified energy conservation projects. For this particular building, the Benchmark Curve represents an Energy Star rating of 8. The Comparison Curve represents an Energy Star rating of 81.

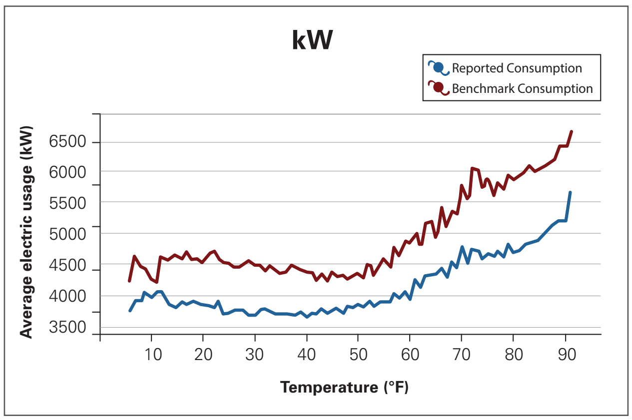


Figure 9: Pathian Analysis comparison chart displaying significant improvements in energy consumption rates over all loads

In Figure 10, the difference curve is shown for the same data set, describing the difference in BAVs at each weather bin. The red curve represents the Benchmark Curve which has been normalized to form a straight line. Note the dramatic difference in the building's energy consumption at each weather bin. In the summer months, the facility has reduced its average energy demand by almost 1,000 kW.

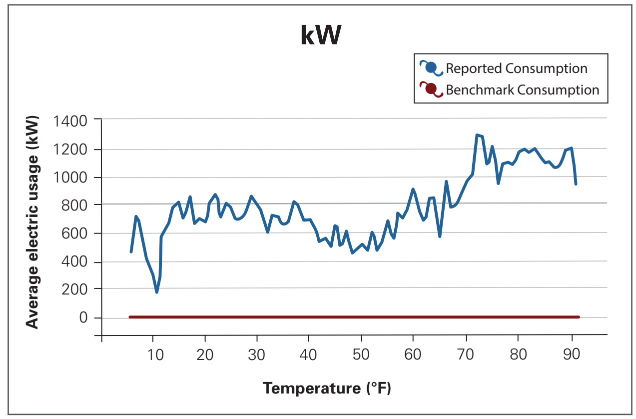


Figure 10: The companion chart of Figure 9, showing the difference in energy consumption between the two periods

Degree-Day Methods vs. Pathian Analysis

Pathian Analysis and degree-day normalization techniques share a common foundation. Each technique claims that energy consumption rate is directly proportional to weather conditions. Pathian Analysis explicitly takes advantage of this by directly measuring energy consumption across small intervals of weather intensity. Degree-days implicitly take advantage of this same relationship, assuming uniformity in the energy consumption rates at different weather conditions. Further assumptions are made that the commercial building will enter heating mode at precisely 65 °F. This isn't true, however, for the overwhelming majority of commercial buildings and can lead to inaccuracies in energy calculations. The degree-day process forces us to make assumptions if we want to keep the measurement and verification process simple.

Therefore, a choice must be made between simplicity and accuracy. If a higher degree of accuracy is required, standard assumptions being made must be mathematically eliminated. This can be difficult to carry out, and field testing is required in most cases. A valid accuracy test of weather normalization techniques must consider all influences on energy use, including variations in weather. This requires someone of skill to perform these calculations, and it can be cost-prohibitive to perform. The federal government, energy service companies (ESCOs) and others have developed energy simulation tools for the purpose of weather normalization, but this is far from a standardized process. The advantage Pathian Analysis has over the degree-day technique is it requires zero assumptions to normalize differences in weather. Using Pathian Analysis, interval weather bin benchmarks precisely describe the performance of the energy system over all-weather loads. No further weather normalization is required.

Standardized Units of Measurement, Precise Results

In the simplest of terms, there are three primary variables required to calculate energy consumption using traditional benchmarking techniques (i.e., degree-day based methods); time, weather and energy. Most would say that weather is the most difficult of these three variables to accurately represent mathematically. It is continuously changing and is never the same from one time period to the next or from one location to another.

The Pathian Analysis technique holds the time period of analysis constant and very small (i.e., less than 15 minutes), essentially making time period a constant mathematical operator, not a variable (i.e., like a day, month, year, etc.). This is the key differentiator in the technique because the result of holding time very small allows us to treat the weather variable as a constant mathematical operator as well. This leaves energy as the only true variable in the benchmarking process. This is important because it eliminates the need to make any assumption whatsoever when using the benchmarking technique to measure and compare our energy consumption habits. The results generated by the measurement process is a precise, real number. Anyone in the world who uses the same data set(s) for analysis will generate the exact same calculated results with pinpoint accuracy. This attribute makes the measurement process an ideal solution for a standardized method to measure and compare our energy consumption habits on a national scale.

Using Pathian Analysis to Compare Peer Group Performance

A peer group can be defined as a building, system or type of equipment with similar function or control strategy. In Figure 11, energy curves for 10 different surgical hospitals are shown to demonstrate how Pathian Analysis can be utilized to compare energy utilization rates among peer buildings, independent of geographic location. Each curve has been normalized to express energy demand in units consumed per square foot. This was done by dividing each hospital's BAV by the building area within each weather bin. This approach allows peer comparison of large buildings to smaller ones. Because they are peer facilities, the energy consumption patterns are very similar. Any peer surgical hospital in the world would have this same general performance profile.

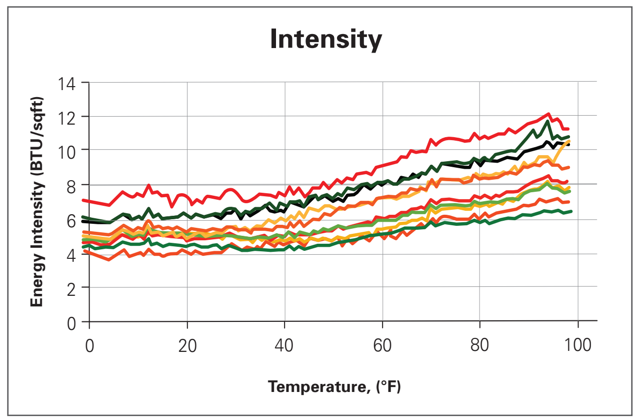


Figure 11: Hospital peer group comparison

The chart shows that energy deficiencies in peer groups are generally consistent across the entire temperature range of analysis. The curve's Y-axis position on the chart is directly proportional to its energy efficiency and has a direct correlation to the commercial building's Energy Star rating. For instance, the top curve on the chart is the least efficient of the peer group. It has a single-digit Energy Star rating. Moving vertically downward, each hospital is slightly more efficient than the next. The lowest curve on our chart is an Energy Star hospital.

Since all the energy curves in Figure 11 are location and time period neutral, any hospital in the world can directly be compared to this peer group's energy consumption habits. This direct comparison would require no assumptions or mathematical corrections to be made for differences in weather conditions among the locations.

In addition, the time period during which the energy data was collected would also have no effect on the comparison results. The data in the charts could have been collected decades apart and it would not have an effect on the analysis or methods used to obtain these results.

Syrx Numbering System, a Catalog for Global Energy Efficiency Performance Standards

The Syrx Numbering System (pronounced Sī-rex) is the first global cataloging system for energy efficiency standards. For peer building classification, the Syrx Numbering System utilizes Standard Industrial Codes (SIC) and the North American Industrial Classification System (NAICS) to categorize each building type.

For HVAC equipment within buildings, the Construction Specification Institute (CSI) Master Format numbering system is used. This allows flexibility to categorize peer groups at each component level (i.e., building, system or equipment type). In the Syrx Numbering System, a "component" can be virtually anything that consumes power or controls the consumption of power (i.e., fan or pump type, hydronic coil, an HVAC control sequence, valve position, on/off status, any set point or numeric value, control loop speed, etc.). This approach allows Pathian to create an endless hierarchy of globally applicable indices for peer group performance standards. Presently, there are more than 23,000 component ID categories used in the Syrx Numbering System. The numbering system not only describes what type of component is being measured but it also categorizes the different control methods used to control how the component operates. An example of this numbering system is shown in Table 1, illustrating how CSI Master Format number 23 34 13, Axial HVAC Fans, are cataloged in the Syrx Numbering System. The Syrx number assigned to an axial return air fan equipped with VFD that is controlled by Pathian Optimal Building Pressure Control (POBPC) fan tracking method using a static reduction control algorithms is 23 34 13 002 003 006.

Table 1: Example of Syrx numbering system cataloging of control methods for axial fan

Section
23 34 00 HVAC Fans
Equipment
23 34 13 Axial HVAC Fans
Fan Type
23 34 13 001 Supply Air Fan
23 34 13 002 Return Air Fan
Fan Volume Control
23 34 13 002 001 RAF – Constant Volume
23 34 13 002 002 RAF – Inlet Guide Vane Volume Control
23 34 13 002 003 RAF – Variable Frequency Drive Volume Control
Control Method
23 34 13 002 003 001 $RA_{cfm} = SA_{cfm} - EA_{cfm}$
23 34 13 002 003 002 $RAF_{spd} = SAF_{spd} * \%$
23 34 13 002 003 003 RA Plenum Two-Thirds Transmitter
23 34 13 002 003 004 RAF Discharge Plenum Pressure (Non-POBPC)
23 34 13 002 003 005 POBPC
23 34 13 002 003 006 POBPC w/Static Reduction
23 34 13 002 003 007 Other
23 34 13 002 003 008 Unknown
23 34 13 003 Relief Air Fan
23 34 13 004 Exhaust Air Fan
23 34 13 005 Outside Air Fan

Peer Group Performance Indices — The Power of Pathian Analysis

A Pathian Performance Index™ (PPI™) is a peer group performance index represented by a single Pathian Curve that precisely describes the performance of a peer group over all weather conditions. A PPI is used to describe the average or best in class performance of any peer group cataloged in the Syrx Numbering System. These energy curves are applicable to any peer building or mechanical system in the world and represent the world's first Global Energy Efficiency Performance Standards (GEEPS) of their kind.

There are two types of performance indexes: Average Pathian Performance Indices™ (APPI™) and Best-in-Class Pathian Performance Indices™ (BICPPI™). An APPI is a Pathian Curve representing the average performance within the peer group. The BICPPI is a Pathian Curve representing the best-performing peer within the peer group. Each of these is discussed further below with an explanation of how these indices can be used to conduct automated energy audits, ongoing commissioning and real-time fault detection of mechanical system assets.

The Average Pathian Performance Index (APPI)

An APPI is a weather-normalized performance standard that intuitively describes the average performance for any peer group without making a single weather-based assumption to derive the energy curve. Only energy data certified by Pathian engineers can be used to create these indices. They apply directly to any member of the peer group, regardless of the member's location or the time period of energy data accumulation.

An APPI curve can be described mathematically by a single data array as follows:

(5) $APPI = GBAV_1; GBAV_2; GBAV\ldots_n$

Where: $GBAV_{1,2,n}$ = Peer Group Bin Average at Each Individual Weather Bin

To calculate an APPI, the GBAV is calculated for each separate weather bin for all data sets within the peer group as follows:

(6) $GBAV_1 = \Sigma BAV_1 / \Sigma BAV_1$ Sample Count

(7) $GBAV_2 = \Sigma BAV_2 / \Sigma BAV_2$ Sample Count

(8) $GBAV_n = \Sigma BAV_n / \Sigma BAV_n$ Sample Count

In simpler terms, the GBAVs are summed within each separate weather bin and then divided by the count of peer components within that group. These indices represent the most likely average performance of a peer group. For instance, say we have 1 million HVAC return air fans all using air flow monitoring station algorithms to control the fans speed (i.e., Syrx # 23 34 13 002 003 001 in Table 1). This index would perfectly describe the average performance of this peer group. An energy manager could refer to this index to understand how his exact same peer equipment is performing in relation to all other fans around the world with similar function and control strategies. This can be done automatically in the form of an equipment variance report where the results of the analysis would be expressed in energy units and dollars. This is a new and very powerful tool for energy managers.

The Best-in-Class Pathian Performance Index (BICPPI)

A BICPPI is a weather-normalized performance standard describing how the most efficient HVAC systems perform within any peer group. As an example, it is desired to compare peer groups of chilled water plant systems based on their pumping arrangement to determine the best-in-class performance. Table 2 shows the Component ID table for classification of three major types of chilled water plant pumping systems of various sizes.

Table 2: Example of Syrx numbering system cataloging of control methods for chilled water plants

Component ID	Component Description
23 60 00 001	Central CHW Plant
23 60 00 001 001	Primary CV/Secondary VV
23 60 00 001 001 001	Central CHW Plant, Primary CV/Secondary VV, <250 Tons
23 60 00 001 001 002	Central CHW Plant, Primary CV/Secondary VV, 250–500 Tons
23 60 00 001 001 003	Central CHW Plant, Primary CV/Secondary VV, 500–1,000 Tons
23 60 00 001 001 004	Central CHW Plant, Primary CV/Secondary VV, 1,000–1,500 Tons
23 60 00 001 001 005	Central CHW Plant, Primary CV/Secondary VV, 1,500–2,000 Tons
23 60 00 001 001 006	Central CHW Plant, Primary CV/Secondary VV, >2,000 Tons
23 60 00 001 002	Primary CV/Secondary CV
23 60 00 001 002 001	Central CHW Plant, Primary CV/Secondary CV, <250 Tons
23 60 00 001 002 002	Central CHW Plant, Primary CV/Secondary CV, 250–500 Tons
23 60 00 001 002 003	Central CHW Plant, Primary CV/Secondary CV, 500–1,000 Tons
23 60 00 001 002 004	Central CHW Plant, Primary CV/Secondary CV, 1,000–1,500 Tons
23 60 00 001 002 005	Central CHW Plant, Primary CV/Secondary CV, 1,500–2,000 Tons
23 60 00 001 002 006	Central CHW Plant, Primary CV/Secondary CV, >2,000 Tons
23 60 00 001 003	Primary VV
23 60 00 001 003 001	Central CHW Plant, Primary VV, <250 Tons
23 60 00 001 003 002	Central CHW Plant, Primary VV, 250–500 Tons
23 60 00 001 003 003	Central CHW Plant, Primary VV, 500–1,000 Tons
23 60 00 001 003 004	Central CHW Plant, Primary VV, 1,000–1,500 Tons
23 60 00 001 003 005	Central CHW Plant, Primary VV, 1,500–2,000 Tons
23 60 00 001 003 006	Central CHW Plant, Primary VV, >2,000 tons

In this case, we want to know the most efficient primary constant volume (CV)/secondary CV chilled water plant with a total capacity of between 1,000 and 1,500 tons. Within the Pathian database, this means a comparison of Pathian Curves generated from total plant kW/ton energy point values for Syrx account numbers containing 23 60 00 001 002 004 as a component ID and chiller plant efficiency. The curve with the lowest overall kW/ton value represents the BICPPI for that peer group.

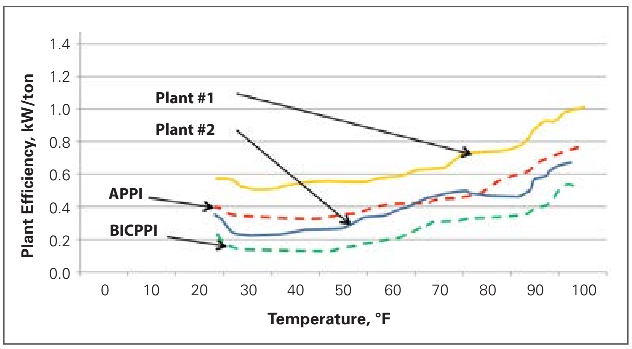


Figure 12: APPI and BICPPI curves

Figure 12 shows this comparison graphically. For this peer group comparison, performance data for two peer chilled water plants (Plants No. 1 and No. 2) have been collected and plotted. Within the Pathian database, both peer group APPI and BICPPI curves have been generated for comparison. Compared to the BICPPI plant efficiency curve, both Plant No. 1 and No. 2 can make significant improvements in energy efficiency through operational and/or equipment efficiency improvements.

Superior Big Data Processing Speed

Perhaps the single greatest attribute of Pathian Analysis is the process speed at which peer group performance comparison data can be analyzed. This is possible because each Pathian Curve can be perfectly described by a single data array (i.e., one record). Thus, only two data array are required to make a comparison using this measurement and verification technique. Since Average Pathian Performance Indices (APPI) and Best-in-Class Pathian Performance Indices (BICPPI) are represented by Pathian Curves as well, either of these can be compared against any peer in the world using just two data arrays. This makes it an ideal solution for smartphone mobile device deployment or other applications that have limited processing power.

Automated Energy Auditing, Ongoing Commissioning and Fault Detection

As APPI and BICPPI curves are generated and catalogued for peer groups within the Pathian database, the ability to provide automated energy auditing, continuous commissioning and fault detection is streamlined into a single application.

Automated Energy Auditing

In Figure 13, the BICPPI curves are shown for two different types of chilled water plants: a primary/secondary constant volume plant (CV) and a primary/variable volume plant (VV). A third plant efficiency curve is plotted for a new customer's plant to determine the potential savings opportunity. With this data, potential savings can be estimated precisely by using the difference in kW/ton values and multiplying that difference by the plant's load and operating hours at each weather bin. A similar approach can be applied to any measured value used to establish peer groups (i.e., buildings, equipment capacity ratios, etc.) to estimate potential energy savings.

For the most accurate estimate of savings, it is desirable to obtain at least one year of measurement data, since one complete year of data will show differences across the desired temperature range. However, it is also possible to evaluate potential savings based on as little as one month of trend data. Typically, the difference in values shown within a smaller temperature range is consistent with differences across the entire range. These results can be extrapolated to provide estimates of savings sufficient for capital decision making when time is more limited for data collection.

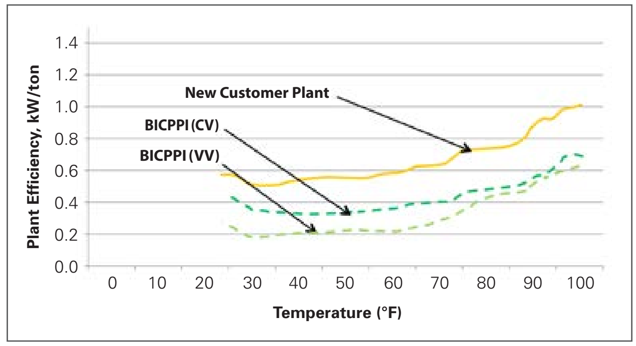


Figure 13: Using BICPPI curves for automated energy auditing

Ongoing Commissioning and Fault Detection

Once a building's equipment performance has been optimized, a Pathian Curve representing the specific component's "fingerprint" is established, and future performance can be compared. Deviations in performance can be caused by many different things, including operator set point changes, modifications of control strategies and degradation of equipment efficiencies. In other cases, original equipment has been replaced with more efficient equipment as part of an energy conservation measure. These deviations in performance can be identified and differences in energy consumption quantified by comparing Pathian Curves from different time periods.

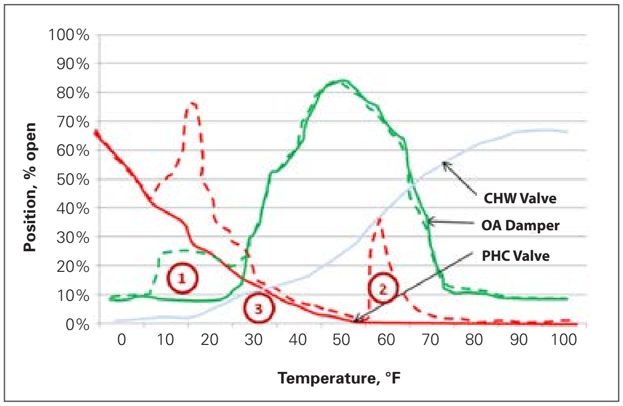


Figure 14: Using Pathian Curves for Ongoing Commissioning and Fault Detection

In Figure 14, the positions of an AHU's outside air (OA) damper, preheat coil (PHC) valve and cooling coil valve have been plotted for comparison years. In each case, the solid line represents the baseline year and the dashed line the comparison year. There are several conclusions that can be drawn from the Pathian Curves plotted for each component. First, the OA damper position has trended to 25% open below a temperature of 30 °F (1), resulting in excess heating of outside air. As a consequence, the PHC valve position for this same temperature range has opened to provide additional heating. Secondly, between 55–70 °F (2), the PHC valve is open, indicating a possible change in control setpoints or a potential maintenance issue. Finally, between 20–50 °F, both the PHC and chilled water (CHW) valves are open (3), indicating competing energy and an opportunity for energy savings. In each case, the deviations are not one-time occurrences, but trends in performance based on the recorded BAVs for that component for the comparison year.

As can be seen from these scenarios, Pathian Analysis techniques can be used as an ongoing commissioning and fault detection application. This can help sustain efficient equipment performance, identify maintenance issues and quantify the value of losses in dollars, providing documentation to support justification with much less effort.

Peer Group Comparison — Beyond the Building Level

As shown in previous examples, it was demonstrated how Pathian Analysis can provide peer building comparisons using interval data from building utility meters. The capability to develop peer comparisons for HVAC systems, equipment and control strategies from a building's DDC system data, however, is the key differentiator between Pathian Analysis and other techniques available in the HVAC industry today. To support this, Pathian has developed several peer group comparison methods applicable to building HVAC systems as follows:

- Peer Equipment Benchmarking
- Position Benchmarking
- Load-to-Position Benchmarking
- Control Sequence Benchmarking

Peer Equipment Benchmarking

As with buildings, peer equipment benchmarking requires size normalization for a proper comparison. In the case of buildings, each building's BAV is divided by its building area to normalize based on energy use intensity (EUI). For equipment, the design motor ratings, cooling and heating loads are the key variables which must be normalized to compare performance of dissimilar-sized peer equipment types. Pathian developed the Capacity Ratio (CR) as the standard method for peer equipment comparison. The CR is simply the measured operating load of the equipment divided by its rated capacity, with the calculated value expressed as percentage (%). For any energy-consuming equipment where the Pathian Curve has been generated, dividing each BAV (kW, Btu/hr, etc.) by the equipment's design capacity (of the same units) yields the normalized Pathian Curve for CR.

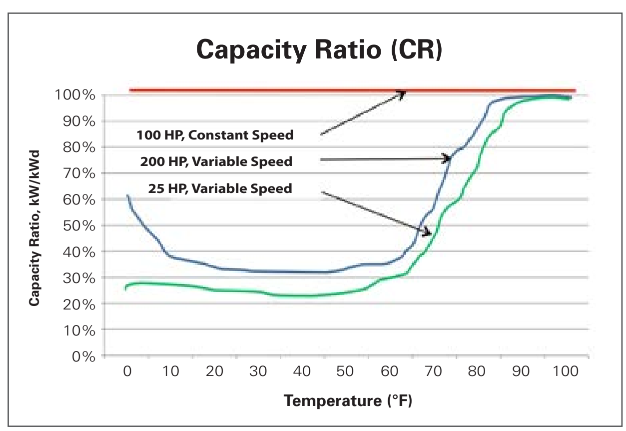


Figure 15: Capacity ratio for supply fans

Figure 15 shows sample CR Pathian Curves generated for three air handling unit (AHU) supply fans with different motor sizes. Two of the supply fans are variable speed, while the other is a constant speed drive. The CR Pathian Curve provides insight into how each fan operates with respect to weather conditions. When comparing peer groups of fans with similar control strategies, differences in CR values at similar weather conditions demonstrate potential inefficiencies which can be used to calculate potential energy savings. Year-to-year comparisons of the same fan can show the impact of system control changes, allowing the ability to quantify energy consumption increases/decreases more cost effectively.

Position Benchmarking

HVAC systems utilize various positioning devices for building temperature control, including fluid control valves and air dampers. Positional data from the DDC system for these control devices can also be used to plot Pathian Curves, providing insight on how equipment is being controlled. For example, Figure 16 shows typical Pathian Curves for an outside air damper and two coil control valves. Once established, these "Positional Benchmarking" curves can be used to identify variations in annual performance, competing energy, and other operational anomalies related to damper and coil valve positions.

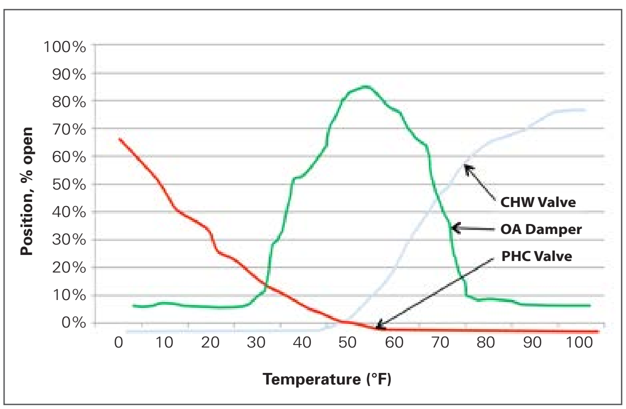


Figure 16: Position Benchmarking Curves for valves and dampers

Load-to-Position Benchmarking

One advantage to utilizing CR for equipment size normalization is the ability to develop load-to-position benchmarking profiles for major HVAC equipment. By normalizing equipment performance on a 0–100% load scale, curves for CR can be superimposed on Positional Benchmarking curves to examine relational characteristics among control valve positions, damper positions and equipment loads. As an example, in Figure 17, a CR curve for a supply fan is added to the Positional Benchmarking curves shown in Figure 16. Additional CR curves for an AHU's return fan, heating and cooling coils as well as positional curves for relief and return dampers can be combined to develop a more complete Load-to-Position composite curve for the specific AHU. The Load-to-Position composite curve provides a graphical "fingerprint" representing the performance of the AHU's control system parameters across all temperatures for the given time period. Once an optimized "fingerprint" has been developed, deviations in equipment performance can quickly be identified from one time period to another.

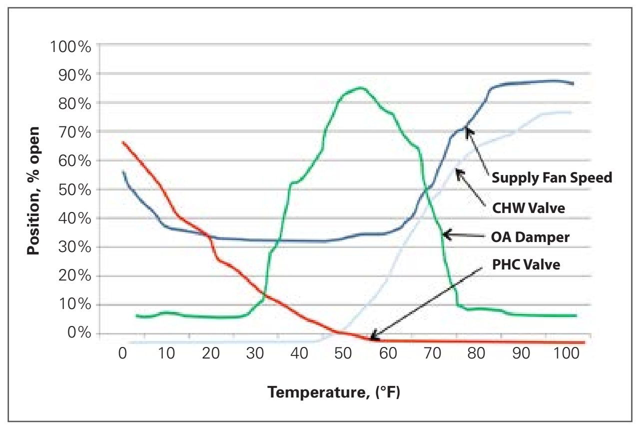
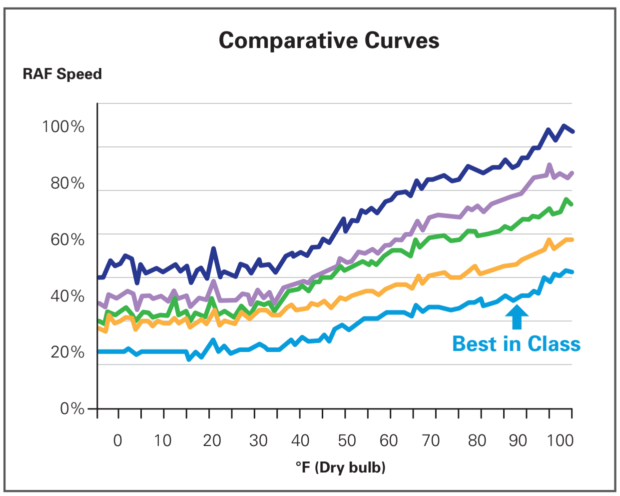


Figure 17: Load-to-Position Benchmarking curves for fans, valves and dampers

Control Sequence Benchmarking

Control Sequencing Benchmarking compares the energy consumption of an existing mechanical system control sequence method to a best-in-class control sequence for that equipment peer group. The generation of a Load-to-Position composite curve for any type of equipment provides a graphical "fingerprint" for how that equipment responds to control parameters across all temperatures. As equipment control sequences are optimized, the "fingerprint" can then be used to compare year-to-year performance changes, which helps sustain optimal performance for that particular equipment. Even more powerful, the "fingerprint" can be compared to other peer equipment with different control strategies, establishing the ability to identify the most efficient control strategy. Creation of these best-in-class performance control sequences provides the ability to conduct automated energy auditing. An example of this is shown in Figure 18. In this case, the speed of AHU return fans is compared for different return fan control strategies.



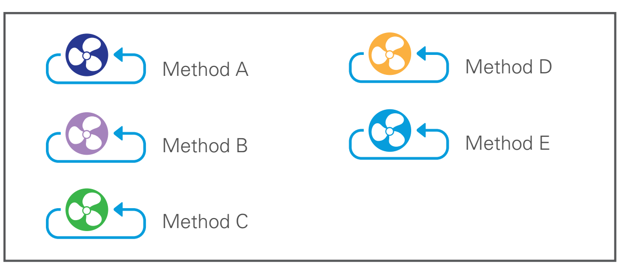


Figure 18: Control Sequence Benchmarking for different return fan control strategies

Creating Smart Meters From Building DDC Systems

Over the past several years, the use of interval data meters to measure building utility consumption has become common practice and is one of the primary sources of energy data for building level analysis. The primary data source for building HVAC equipment is the building's existing DDC system. Pathian Analysis allows cost-effective transformation of thousands of DDC points into virtual smart meters by streaming the Current Operating Value (COV) of any DDC point type to our cloud-based data servers.

To organize this data, the first step in this process is to develop a building-specific directory or object tree for the HVAC equipment within the building (i.e., chillers, boilers, AHUs, pumps, etc.). Once the object tree is completed, Pathian uses the Syrx Numbering System to assign DDC points associated with each piece of HVAC equipment with a unique identification number based on its customer, equipment tag, component ID and point type. Each Syrx account number is then matched (or mapped) to the DDC point name as defined by the building control system manufacturer. For a typical 1 million square foot building, this equates to approximately 1,500 DDC points. The amount of data points streamed depends on the end-user requirements and the type of analysis being performed.

Once mapped, the COV of each DDC point is recorded every 15 minutes. The data is received in the form of a CSV file, using HTML XML posting method to transfer the data. Currently, Pathian has the capability to collect and process data from all major HVAC control system manufacturers.

Differentiating Pathian Performance Index (PPI) From Traditional Energy Simulation Tools

The single greatest differentiator between PPIs and traditional energy conservation simulation tools like DOE's eQUEST is measuring actual vs. predicted performance. Simulation tools are used to predict energy savings for implementing energy conservation measures (ECM) based on user-defined model inputs such as equipment type, equipment efficiency, operating hours, control setpoints and historical bin weather data. Assumptions made during model development, however, do not always reflect actual conditions for peer types of equipment once the equipment in placed into operation. This leads to unexpected shortfalls in actual vs. predicted savings for the ECM. In contrast, the PPI is a historical average generated from actual performance data for hundreds or thousands of systems and/or equipment within the peer equipment group for that ECM. Utilizing this approach, more accurate predictions can be made to assess potential energy savings for the chosen ECM. Also, by continuously measuring performance, deviations in system performance over time can be proactively identified and corrected to reduce risk of not achieving savings goals.

Conclusion

HVAC mechanical system energy efficiency is driven not only by the efficiency of the equipment installed, but more importantly by the choices made in how these systems are operated and controlled. But what works best? And how can we know for sure? Data to validate these choices are now readily available via utility smart meters and advanced building management and control systems. The ability to process large amounts of data has increased exponentially in the past decade. Absent is an application that can cost-effectively organize and process this data into meaningful and actionable information for use in the HVAC energy management industry. Pathian Analysis is the solution to systematically identify and quantify the benefits of implementing best practices through HVAC system optimization.