How Electrical System Monitoring Improves Facility Efficiency, Reliability and Safety

David G. Loucks
Eaton Corporation

Gregory F. Reed
University of Pittsburgh

Abstract:

Electricity is the lifeblood of modern society, and certainly of nearly any commercial or industrial operation. And similar to our bodies, we can learn much by examining this "blood" more closely. In a parallel with a human body's circulatory system, changes in electrical flow can tell us whether our (electrical) system is functioning and healthy. The trick for our facilities, though, is to not always require someone with a doctorate level knowledge to recognize the problem. This paper discusses advances in machine diagnostics that are for the first time being applied to electrical systems. These advances are reducing operating costs by both decreasing energy consumption, as well as increasing the "life expectancy" of equipment -- all through the use of electrical system data to recognize tell-tale changes within equipment.

Introduction

Metering devices are common in facilities. Meters measure WAGES (water, air, gas, electricity, steam) consumed and establish the bill charged for those items. In the US, buildings consume over 70% of all electrical energy generated and owners of buildings pay for over 80% of the all US expenditures for electricity [1], implying that even small errors can result in large expenses. To protect their interests, the metering device is provided by the utility billing for the service. Some owners install their own metering. Sometimes this metering is used to double-check the utility billing, although typically a utility bill is accepted at face value. More frequently, customer metering is used to "sub-meter" loads to allocate energy costs by department or by type of load (e.g. HVAC, lighting, plug-loads, specialty machinery, etc.). By measuring energy by type of load and comparing it to expected or promised consumption, returns on investments made in energy saving solutions, such as lighting retrofits, can be verified. These sub meters typically collect and report values needed to calculate an energy bill by including data such as present demand, power factor, and accumulated values such as energy or peak demand.

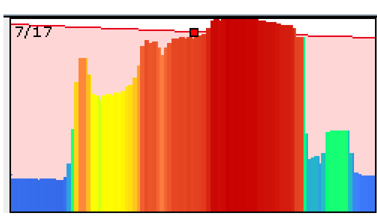
However, meters are used for more than just energy billing or energy consumption verification. Energy engineers examine energy consumption patterns and look for abnormalities that signal areas of concern. Energy engineers look for ways of reducing peak demand (kW or MW) and reducing energy consumption (kWh or MWh), with additional potential savings coming from reducing penalties from poor power factor or potentially poor power quality (harmonic distortion) which often plagues many older facilities.

Savings opportunities change as energy consumption changes. Energy consumption changes as work type or quantity changes or as seasonal weather changes. Work type or quantity may change based on the hour of the day, the day of the week or the season of the year. Seasonal weather data is available in real-time, historical or predictive (up to several days in the future).

Consider a typical commercial facility that houses people, computers, lighting, HVAC and various miscellaneous loads. Trends of power usage collected during 15-minute utility demand windows can be built on total facility load or individual loads. Depending on the level of sub-metering installed, trends can be established for types of loads, building wings, floors, departments or any other location or application specific measurement. By examining these trends, a pattern may emerge signaling unusual energy or power (demand) consumption.

Figure 1 –Energy Monitor Pattern Tracking Software

Figure 1 shows a screenshot of a computer program [2] that displays and normalizes power demand during each of the potential 96 15-minute demand windows that occur during a 24 hour period (96 = 24 hrs/day * 4 windows/hr). Warmer (redder) colors correspond to higher values of demand. Focusing on the reddest of the red bars in Figure 1, July 17 quickly stands out.



07/17/2012 Tues

Day Stat	07/17	Base
Max KW	1048.05	898.03
Min KW	176.03	173.64
Average KW	648.97	564.76
Energy MWh	15.58	13.55

Figure 2 – July 17 detail

Figure 2 displays a zoomed-in view of the 24-hour period beginning at 00:00 hours on July 17 and continuing to 23:59 hours on the same day. Note that the peak demand, month to date, is 1048.05 kW (red arrow in Figure 2), a value that was 16.71% higher than the average demand for that day of the week at that hour of the day. Figure 3 shows that this monthly peak demand occurred during the 14:15 to 14:30 demand window.

Time	Cherrington Meter (KW)
Jul 17 13:15:00	1030.99
Jul 17 13:30:00	1033.27
Jul 17 13:45:00	1027.28
Jul 17 14:00:00	1032.16
Jul 17 14:15:00	1048.05
Jul 17 14:30:00	1041.32
Jul 17 14:45:00	1041.71

Figure 3 – Peak demand of 1048.05 kW recorded on Jul 17 during the 14:15 to 14:30 demand window

This information, while valuable, is somewhat like driving an automobile using the rear-view mirror. Trends are shown, but what would be more useful would be some indication of problems ahead, preferably before they have been “run into”. However, since the historical consumption by day, season, and time of the day is known, can this information help to predict if a new peak demand might occur later that same day?

Consider the scenario as shown in Figure 4. The x-axis corresponds to time of day (extreme left = 00:00 hours, and extreme right = 23:59 hours on 7/17). The y-axis displays units of power scaled in units of kW, with the top of the blue trace representing the predicted value of demand for each of the 96 demand windows during that day.

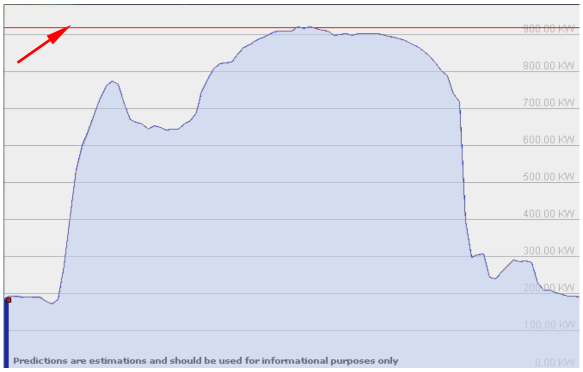


Figure 4 - Top red line is previous peak demand. Blue outline is predicted demand minute-by-minute for that day as of the beginning of the day (0:00 hours).

This algorithm, using historical data sorted and filtered by day of week, season of the year and time of day, predicts the demand (power) requirements that should occur during any particular day, at any particular hour during that day. In this particular facility, the majority of energy consumption tracks the operations which take place mostly between the hours of 5 AM and 7 PM, 5 days a week.

As mentioned earlier, a more valuable implementation of the algorithm would "look ahead". In this particular implementation, the predictor identifies a trend in the data and attempts to extrapolate the trend to the end of the day. A "Now Ratio" argument is used to balance between the short-term trends and the long-term trends. The closer to 0 it is, the more weight is placed on long-term trends. The closer to 1 it is, the more weight is placed on short-term trends. The prediction algorithm can be fine-tuned using one of several models:

- **Average Variance** takes an average between short-term and long-term variances, shifting towards long-term as more data is received.
- **Linear Variance** uses a Now Ratio to balance between short-term and long-term variances.
- **Weighted Variance** - same as Linear Variance, but attempts to reduce extreme predictions.
- **Linear Variance Reset** - same as Linear Variance, but ignores short-term trends after large long-term trend changes.

Notice in Figure 5 that a new thin orange line has appeared on the graph slightly above the light blue border. This orange line represents an "update" of the predicted minute-by-minute demand for later in that day. The update is due to early real-time data coming in higher than the previously predicted values. This leads the algorithm to predict that demand values later in the day should be higher than predicted.

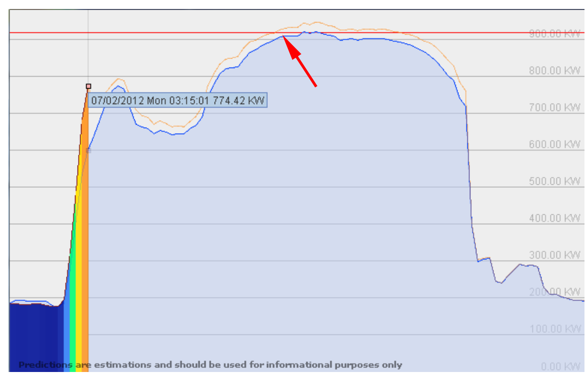


Figure 5 – Red arrow marks the point where the orange line crosses red peak demand indicating a prediction that a new peak demand will be set that day. Substantial advance notice is given as this prediction occurs at 3:15, but the predicted time for the crossing point is nearly 8 hours later (11:00).

Using this predictive capability, the algorithm predicts that a new, higher peak demand will be set at around 11:00 that day, or almost 8 hours into the future. Normally, such advance warning should be plenty of time to take actions to prevent a new peak from occurring.

In this particular facility, no action was taken, and unfortunately, the prediction turned out to be true.

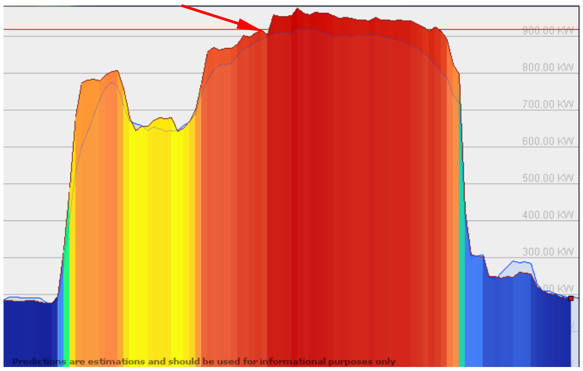


Figure 6 – At exactly the predicted time (11:00), the facility set a new peak demand

At this site, demand was billed at $12/kW, meaning this excursion past the previous peak demand resulting in an additional $600 being added to that month's energy bill. In many utility rate structures, this new demand "ratchets", resulting in "billed demand" in subsequent months exceeding "actual demand", increasing the costliness of this excursion even further. In facilities such as this, light levels could have been reduced, temperature setpoints could be have been increased, non-essential loads could have been switched off, or work could have been shifted.

Based on the time of the year that this new peak demand was set, it is almost certain that higher outside temperatures placed greater demands on the HVAC system, resulting in a new peak demand. To verify, the power data should be divided by (normalized) temperature (or more correctly cooling degree days). Even for facilities that do not sub-meter HVAC and so do not have a broken out measurement for the percentage of electrical power consumed in the HVAC system, a simple ratio of total facility electrical energy consumed divided by the total degree-days over which that energy was consumed can provide a useful metric that can establish a baseline "efficiency" of the HVAC system. This method works if the balance of the load can be predicted using one of the linear prediction methods supported by this software. Large, random balance of system load swings color the data measured by the single service entrance meter and reduce the correlation of the HVAC load with the total load measured by the service entrance meter. For applications without large random load swings in the balance of the facility loads, the service entrance meter normalized to outside temperature can be used as inputs to this simple linear prediction model. When the ratio of cooling energy consumed per degree-day deviates from a linear trend line, this change can indicate degradation within the HVAC system.

Outlier Detection

Up to this point, the data has been used to identify opportunities to reduce coincident peak demand (multiple loads operated simultaneously). However, recognizing patterns in energy consumption can also improve equipment reliability and safety by detecting changes in how equipment operates. If equipment is operating at unusual times or for unusual lengths of time, does this indicate a change in work processes, perhaps leading to an inquiry of whether proper procedures (including safety) are being followed?

For example while the data shown in Figure 6 shows higher than expected energy consumption would it be correct to say that this consumption was unusual? Possibly not. Since this data was not normalized to weather, and since a large portion of building energy consumption is used by HVAC, it is entirely possible that the increased energy consumption was simply due to weather. In this case, the new peak demand exceeded the previous peak demand by 6%, something that may by perfectly expected due to hotter weather.

However, if the data were examined another way, would there be a way of detecting abnormal energy consumption? One change to the algorithm would be to look for times and days when the percent difference between the real-time and the predicted loading deviated by some larger amount. When those deviations are stacked ranked, the greatest deviation could be an indication to investigate further.

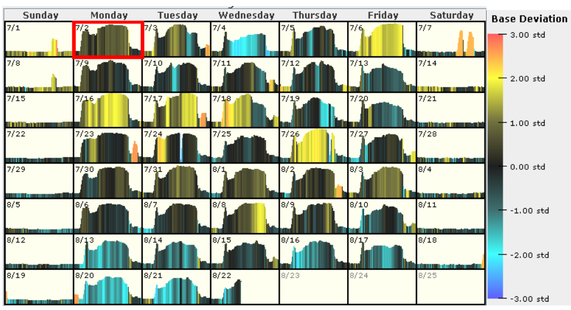


Figure 7 – Same data as shown in Figure 1, except algorithm colors are based on deviation from mean calculated for that day, season and time. Red corresponds to a real-time value that exceeds the predicted value by +3 standard deviations.

In Figure 7 the same data is shown as in Figure 1 except the color coding is changed based on magnitude of deviation of the real-time value from the calculated mean value for that particular day, time and season. The brightest reds correspond to +3 standard deviations above mean and the darkest blue correspond to -3 standard deviations below mean.

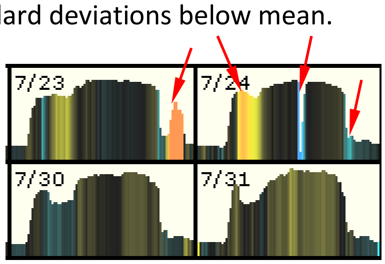


Figure 8 – In this installation, outliers, or unusual loads, don't correspond to highest values.

Figure 8 shows a zoomed in portion of the monthly demand data from Figure 7.

The dark vertical bars in Figure 8 correspond to real-time values of demand that deviate little from predicted mean values. The most interesting colors occur when more (or less) power is used *at unexpected times*. For example, notice the large increase in consumption during late evening of July 23 (first red arrow in Figure 8). The value wasn't unusual in its magnitude, only in its magnitude *for that time*. The next day, the software reported another unusually high pattern of consumption (for the time of day at least), as well as two instances of unusually low energy consumption. Did a machine stop production?

More Advanced Analysis

While these methods are useful, they only hint at the type of analyses possible from post-processing power, energy and temperature data.

A recent patent [3] reveals another method of analyzing data collected from energy and temperature metering and using this data to predict normal or abnormal operation within cooling systems. The problem solved by this patent is the equating the units of "energy" with those of "temperature" (e.g. comparing BTUs or calories or Joules with degrees C or K). In forced air or liquid-cooled system, common among electrical devices and within buildings themselves, more cooling is available from convection that from alternative methods of heat transfer (i.e. conduction, radiation or vaporization).

The analysis begins with a reexamination of the equation for heat transfer by convection, given as:

$$ave(\dot{q}_v) = \boldsymbol{ave}(\boldsymbol{S\eta F}(\Delta T)) \qquad (1)$$

Where:

$\dot{q}$ heat transfer rate via convection
S Specific Heat of cooling media
η Efficiency of heat exchanger
F Flow rate of cooling fluid
ave(distributed average operator[1]

Grouping the potentially more difficult-to-measure parameters together into a single parameter, denoted ε:

$$\varepsilon = S\eta F \qquad (2)$$

The equation can be rewritten:

$$ave(\varepsilon) = \frac{ave(\dot{q})}{ave(\Delta T)} \qquad (3)$$

This equation implies that for a constant cooling fluid rate, constant heat exchanging efficiency, and constant specific heat of cooling media, the temperature rise of an enclosed space is directly proportional to the energy injected into this space.

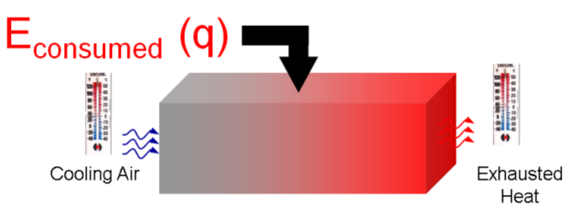


Figure 9 – Simplification of black body cooling model when conduction, radiation, and vaporization effects are ignored.

[1] The average value (mean) of each element enclosed within the parenthesis is calculated prior the calculation of the algebraic equation

For any object with a stable temperature (and ignoring chemical or state change effects), the average amount of heat energy entering an object is equal to the average amount of heat energy leaving.

It could be argued, validly, that ε described in Equation **(2)** cannot be used as a proxy for cooling flow rate since it is affected by heat transfer efficiency. Heat transfer efficiency could be affected by difficult to monitor parameters such as dust or dirt buildup, corrosion or even things such as spider webs built over heat exchangers or cooling fins.

While this is certainly true, the important use of Equation **(3)** is to recognize is that *anything that affects convective cooling will adjust the ratio of heat input divided by the change in temperature inside the object versus outside the object*. In fact, the value of using this insight is that by tracking energy input divided by delta T, changes in the cooling system are now visible. These changes can be seen long before temperature alarms are triggered.

Application Example

Reports published in 2010 claim that data centers were estimated to consume between 1.1 and 1.5% (~200 billion kWh) of all the electrical energy generated world-wide. This percentage has been growing over the last decade 2000-2010 [4]. With such large quantities of energy consumed, energy efficiency techniques targeting this application have the potential to save large amounts of energy consumption. Measurement techniques such as The Green Grid's PUE (Power Utilization Effectiveness) [5] have been developed to help data center operators benchmark the cooling efficiency of their facility against other sites. Reducing the amount of cooling energy consumed within data centers is a key step in lowering the overall energy bill. Unfortunately, while techniques such as PUE can be applied to entire data centers, this technique does not help locate *where* in the data center the cooling problems are occurring.

First, it is important to understand that poor PUE implies that certain sections of the data center are "overcooled." Techniques such as computational fluid dynamics (CFD) can be used to calculate cooling air flows and temperatures across servers, but this technique requires computational horsepower, as well as additional sensor inputs not commonly available as continuous real-time signals in a building environment. Typically CFDs are done as periodic (batch) operations. However, in data centers, changes are occurring all the time. Server loads (and therefore exhausted heat) rise and fall. New servers, storage and networking hardware are installed while other equipment may be de-commissioned.

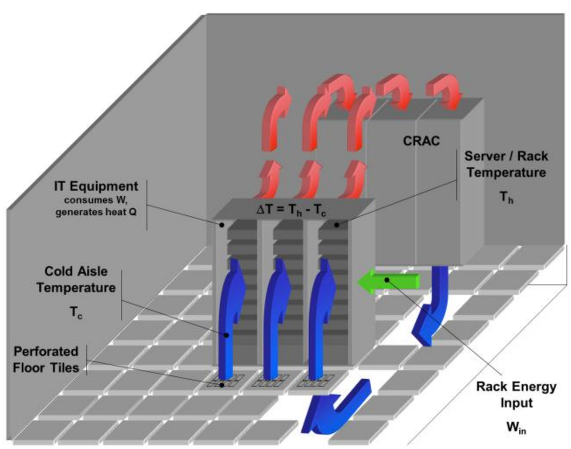


Figure 10 – CFD analysis models airflow volume and temperatures. In data center environments this analysis is used to predict amount of cooling available at particular servers within a data center.

When considering how a data center operator would keep track of cooling system efficiency, what is interesting to note is that the calculation of epsilon (ε) as shown in Equation **(2)** provides a proxy of the cooling system effectiveness at any point within a facility - at least at any point where electrical energy and temperature are measured. In a data center, this information would be available at a server or within a data rack housing groups of servers. If that rack included branch circuit metering of total energy consumption for all loads within the rack and if temperature could be collected within that same rack, all the information necessary to calculate ε would be available. An example of how this might be installed is shown in Figure 11. Trending ε as shown in Figure 12 could then be used to detect degradations in the cooling system, since declining ε indicates a declining "efficiency" in cooling that rack. Combined with PUE data, the data center operator has a tool to locate *where* the cooling inefficiency is occurring and take action to correct the problem. The problem being, typically, that there is too much air flow at that particular rack.

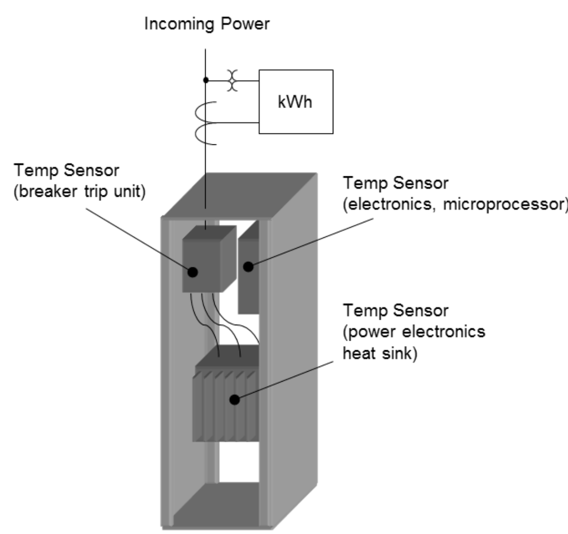


Figure 11 – Sensors required to calculate epsilon (ε), the measurement described in the text that emulates some of the data provided by a CFD analysis.

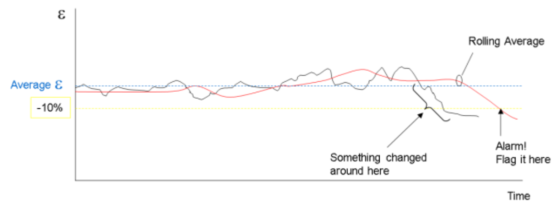


Figure 12 – Changes in ε signal systemic changes in convective heat transfer within the system

Conclusions

Using knowledge gained from the field of machine diagnostics, electrical equipment within facilities can now report not only on how much energy is consumed, but also identify anomalous energy consumption. Using knowledge of proper machine and/or facility operation, malfunctions within particular subsystems can be detected. An example given in this paper was a malfunctioning cooling system in a data center. Degraded cooling systems potentially waste energy, while the opposite problem of insufficient cooling can reduce equipment reliability or life (due to effects predicted by the Arrhenius equation). Premature failure of equipment not only increases costs and decreases the facility's ability to complete its mission, but depending on the type of failure, safety of the facility or persons working within the facility could be affected. Examples of electrical equipment failure causing safety problems include healthcare facilities, aircraft electrical systems, security systems, chemical processing equipment and boiler controls (e.g. power plants). Gaining this level insight into electric system operations for commercial and industrial operations, through advanced diagnostics and condition monitoring, is paramount in universal efforts towards achieving higher levels of energy efficiency.

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[1] http://buildingsdatabook.eren.doe.gov/TableView.aspx?table=1.1.9

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[3] United State Patent, 8,155,922, Loucks, D.G., "*Electrical device cooling efficiency monitoring*", issued April 10, 2012

[4] Koomey, Jonathan. 2008. "Worldwide electricity used in data centers." Environmental Research Letters. vol. 3, no. 034008. September 23. http://stacks.iop.org/1748-9326/3/034008

[5] The Green Grid, "*WP#06-The Green Grid Data Center Power Efficiency Metrics: PUE and DCiE*"

David G. Loucks (SM'2003) is Manager, Power Systems and Advanced Applications for Eaton Corporation's Americas business. Dave received his BSEE from the University of Kentucky, his MSEE from the University of Pittsburgh (power systems analysis and control systems) and is currently a Ph.D student at the University of Pittsburgh researching advanced power systems analysis algorithms. He spent 15 years with Westinghouse in a variety of technical roles prior to the acquisition of the Westinghouse Distribution and Control Division by Eaton in 1994. Since that time he has focused his work on control systems, power systems analysis and business management roles. A former adjunct instructor of electrical

engineering at Geneva College near Pittsburgh, Dave is a registered professional engineer (PE) in Pennsylvania, a Certified Energy Manager (CEM) through the Association of Energy Engineers and has been awarded 8 patents.

Gregory F. Reed (M'1985) is the Director of the Center for Energy's Electric Power Initiative in the Swanson School of Engineering and Associate Professor in the Electrical and Computer Engineering Department at the University of Pittsburgh. He has over 27 years of experience in the electric power industry and academia, including the utility, manufacturing, and consulting sectors at Consolidated Edison Co. of NY, ABB Inc., Mitsubishi Electric, and DNV-KEMA Inc. Reed received his B.S. in Electrical Engineering from Gannon University, Erie PA; his M. Eng. in Electric Power Engineering from Rensselaer Polytechnic Institute, Troy NY; and his Ph.D. in Electrical Engineering from the University of Pittsburgh, Pittsburgh PA. He is a member of the IEEE Power & Energy Society, Power Electronics Society, and Industrial Applications Society, and a member of the American Society for Engineering Education.