

# Bridging the gap from **data to value:**

**3 ways physics-based modeling and a digital twin can help overcome sensor limitations**



**Many facilities use networks of sensors to generate data for monitoring and maintaining assets. The resulting data sets are rich fodder for analyzing system faults and optimizing the ways you manage assets in your built environments.**

It's tempting to think that the more data you have, the better you can perform your duties, and the less susceptible you are to getting blamed for system failures when things go wrong.

## **Key Findings**

- Reliability of end-to-end systems is put at risk by having too many potential points of failure.
- Digital twins and physics-based modeling help reduce sensor counts, identify faulty sensors and eliminate false positives.
- Asset managers can gain a more durable, digital foundation for understanding and mapping processes and priorities.



However, even with all that data, it can be hard to diagnose relevant issues in a timely way. Sensors are an imperfect technology—they can be miscalibrated to send the wrong data, they can send data you don't really care about, and of course, they can weaken and fail. Accounting for the limitations of sensors is an important part of maintaining healthy asset monitoring and management.

One effective way to put sensor data to work in helpful, sensible ways is to apply physics-based modeling and a digital twin as part of your sensor-based monitoring solution. A digital twin is a database that models your installation as a sum of its many components, connections, and characteristics. Without a digital twin, you have no electronic medium for accurately capturing the myriad ways each system part relates to and impacts the other parts so that you can develop meaningful knowledge about them. And where physics comes in is by applying basic physical laws to the data models in your digital twin so that the solution can understand and learn usage patterns that conform to physical logic.

Using these two elements in tandem has plenty of advantages for modernizing your long-term asset management approach. For starters, you can:

- **Reduce sensor count** and thereby save on operational expenses, among other benefits.
- **Identify faulty sensors** and other issues more readily in your environment.
- **Eliminate false positives** so that your monitoring solution gives you better, root cause-focused reporting.

## Fewer sensors, fewer hassles

When the Internet of things (IoT) came along and the notion of 24/7 monitoring promised end-to-end detectability for system-wide issues, facilities everywhere began equipping their systems with sensors everywhere a sensor would fit. The idea was that “more was more”—the more data you could collect about system performance, the more you could do to monitor and maintain the system effectively.

This reasoning was true to an extent, but it came with its own new set of problems. Sensors are physical equipment, and like any equipment, they have a useful lifespan, and over time need to be serviced or replaced. Depending on the nature and complexity of the system involved, this increase in equipment count has a measurable negative impact in a few key areas:

- The expense of buying, installing, and maintaining sensors causes *operating costs* to go up.
- The *reliability* of the end-to-end system is put at risk by having so many potential points of failure.
- Teams see new *efficiency* burdens as the scope of duties for a typical operator is expanded.
- In some cases, *life safety* concerns are an issue, when sensors are located in hard-to-reach places.

In the example shown in Figure 1, the cooling tower in a building contains equipment that exchanges water at varying temperatures and uses a fan to produce cool air for the building. Let's assume that as part of maintaining this system, the operator wants to keep a keen eye on the system's overall power consumption.

The common way of tracking power consumption would be to attach a kilowatt power sensor that sends data back to the operator's monitoring software. But let's say it's difficult to access some portions of the tower where sensors would be required, and the expertise to maintain these sensors means hiring outside contractors every time service or replacement is needed. What if there were a way to get by without using a sensor at all?

By mapping all system elements onto a digital twin, the operator has the data he needs to determine expected power consumption in the tower by reverse engineering basic physics calculations. The temperature differentials of the water entering and exiting the tower provide key factors, along with the known physical properties of the system itself. This in turn lets the monitoring system calculate how hard the tower needs to work to deliver the current cooling level, and the consequent power utilization required for doing so.

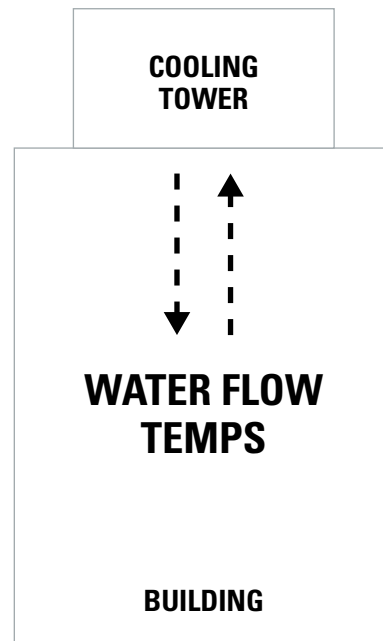


Fig. 1. Example cooling tower.

## Calculating sensor failure points

But sometimes you need sensors anyway, and maintaining them is an inescapable part of your operational duties. A key part of these duties is detecting when sensors fail, along with other possible system faults. Just as physical laws can be overlaid with a digital twin to produce “virtual” sensor results as shown in the previous example, similar principles can be applied to root out the failures of individual sensors and other suspicious conditions within an existing system.

Figure 2 shows a portion of a system where water flows out of two chillers through a single junction. Attached to the junction is a closed valve, and a pipe leading to the next part of the system.

Four flow sensors operate at key points: one for each of the junction intake locations where water flows out of the chillers, one where the water continues out of the junction, and one where the junction connects to the closed valve.

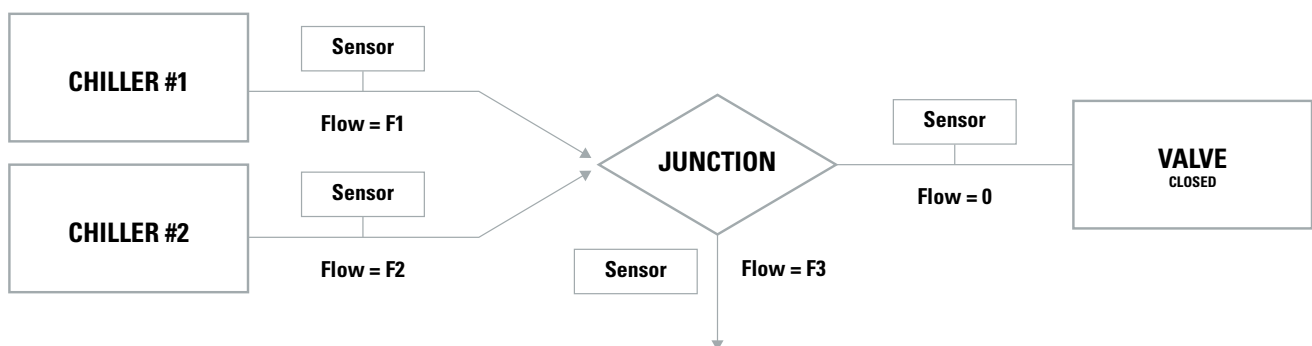


Fig. 2. Example sensor configuration for a chiller flow subsystem.

In this example, applying physics to a digital twin schema can yield data that indicates the system is either in proper operation or out of whack somehow. Physics tells us that the combined flows out of the chillers should total what flows from the other side of the junction, and since the valve is closed, the outgoing pipe should carry that entire flow (minus minor corrections for pipe friction, and so on).

If  $F1 + F2$  equals  $F3$ , the subsystem shown here is in correct operation. But if the monitoring system finds a significant difference between the combined flow in and the net flow out—which it can only do if it's programmed with a digital twin and physics-based rules—it's able to report the anomaly, indicating either a faulty flow sensor, or a leak somewhere in the system, or maybe the "closed" valve isn't fully closed after all.

## Focusing on root cause analysis

One of the key goals of any asset management team is to look for root causes of systemic problems that can impact the performance, reliability, and safe utilization of the assets they oversee. What often

gets in the way of this analysis is the proliferation of "false positive" alerts, where the monitoring system thinks it has detected a problem, but it's either not a problem that has business impact, or it's not actually a problem at all.

Finding efficient ways to monitor your systems means, in part, rooting out these false positives so you can stay focused on the system behaviors that matter most for your purposes.

Let's return to the cooling tower in the first example. As we discussed, your goal is to monitor power consumption and make sure it stays within a reasonable operating range. Now let's say you need to perform this monitoring across several cooling towers, located in different buildings. The towers at each building perform similar functions using similar systems, as shown in Figure 3.

Equipping the buildings with sensors is one option for gathering data and analyzing for root cause. But sensor data is typically a barrage of numbers, only a few of which might be pertinent for your purposes. Machine learning and rules-based programming of

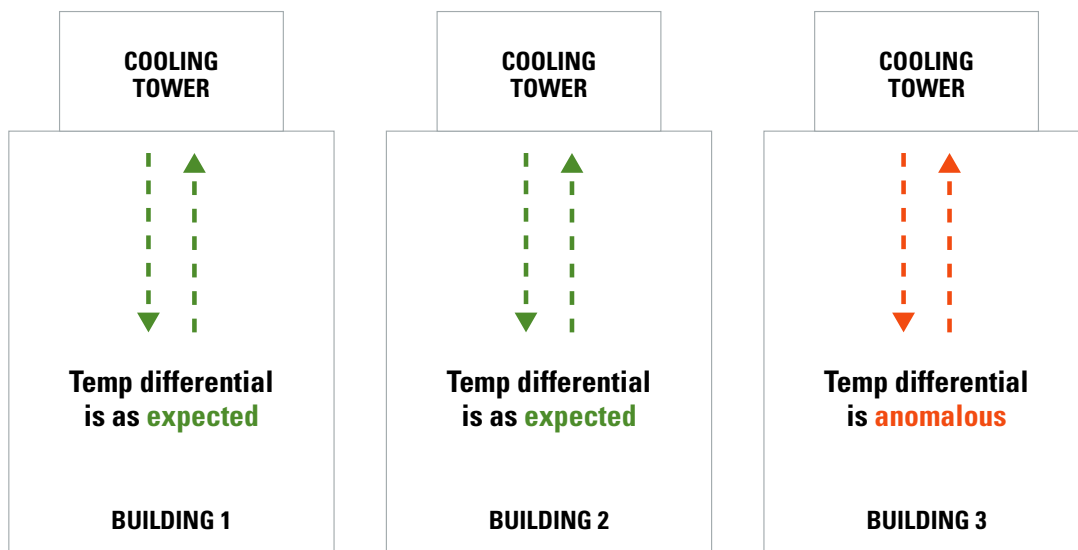


Fig. 3. Example array of cooling towers with an anomalous result at one of the buildings.

your monitoring solution can help identify statistical anomalies in these numbers, but the resulting alarms and alerts are often irrelevant to the actual business conditions you're monitoring for—in this case, variances in power consumption.

Using the same logic we applied in the first example, and repeating it across multiple facilities, can serve to identify these anomalies in a simple, meaningful way. Tracking the temperature differentials in each tower and using physics to compute the power consumption at each one gives you a basis for singling out anomalous readings that are actually pertinent to your business needs. In this example, an atypical reading at building 3 indicates an issue.

Once again, this approach only works when you create a digital twin and use a physics-based approach to modeling potential error conditions in your environment. The advantages to doing so help simplify the monitoring process, filter out the “noise” of false positives, and gain a more durable, digital foundation for understanding and mapping the processes and priorities you care about day-to-day.

## About Tignis

Seattle-based Tignis provides unique physics-driven analytics for connected mechanical systems, utilizing digital twin and machine learning technologies. Tignis increases the reliability of connected mechanical systems by automatically monitoring and learning, continuously detecting threats to reliability—even on diverse and complex systems, and precisely identifying and predicting operational impacts. Tignis enables you to simplify system monitoring processes, filter out the “noise” of false positives, and gain a more durable, digital foundation for understanding and mapping the processes and priorities you care about day-to-day.

**For more information on applying physics-driven analytics to your systems monitoring data, visit [www.tignis.com](http://www.tignis.com)**