The Brainlike Advantage

Studies have shown that Brainlike sensing can add major value in many critical monitoring applications, including the following:

- Security threat surveillance.
- Environmental health monitoring.
- Equipment health monitoring.
- Human health monitoring.

In all such applications, Brainlike sensing adds value by greatly improving monitoring effectiveness and substantially reducing total operating costs. This report illustrates a major Brainlike advantage: being able to deliver *precise* monitoring automatically and efficiently, under continuously changing conditions.

This report illustrates the Brainlike advantage using data from an electricity monitoring application. The same advantage holds in many other critical monitoring applications, including all of those listed above.

The Figure 1 plots illustrate electricity demand under normal as well as unexpected operating conditions. The blue plot shows electricity demand values measured every 15 minutes over a three-month period. The magenta plot shows how electricity demand might look if a costly incident occurred during the last month of the same period.

Like many other incidents, the one shown in Figure 1 develops in such a way that for a brief period of time, action could be taken to prevent a costly incident from occurring. In particular, the figure shows sharp but brief increase in demand over a two hour period, followed by a steep drop to a very low level.

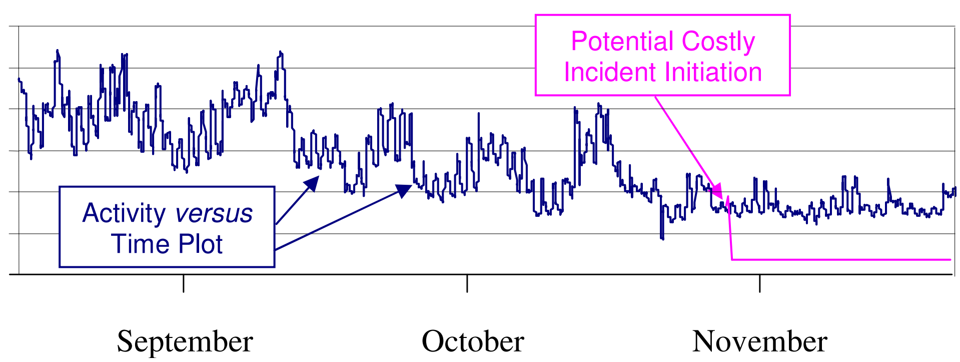

Figure 1. Normal Activity and Costly Incident Plots

The Figure 1 excursion might occur if a transmission line breakdown slowly developed over the two hour period. If the excursion were found and corrected during that period, normal operation could be restored as indicated by the blue plot continuation after the incident initiation. If left unnoticed and uncorrected, however, a total transmission line breakdown could occur as indicated by the steep drop in the magenta plot. The key Brainlike advantage is its unique capacity to identify incidents like this one within that short time before they become costly, for reasons that will be explained next.

Like many other types of monitored data, electricity demand varies substantially over time, as shown in Figure 1. Demand tends to be higher during peak demand hours; demand is often lower on weekends than on weekdays; demand varies with temperature; demand changes systematically while weather fronts are passing through the region; and demand varies as seasons change. Moreover, daily demand profiles and temperature-demand relationships are different in warm seasons when higher temperatures produce higher air conditioning demand, than in cold seasons when higher temperatures produce lower heating demand. In short, electricity demand, like many other monitored activities, is highly non-stationary and very complex. This non-stationary behavior that is so typical of monitored data is hard to predict and very difficult to monitor.

All monitoring methods compare observed values to expected thresholds under normal operating conditions. Alarms are produced when threshold values are exceeded. Figure 2 shows how simple monitoring methods use fixed thresholds, and it shows why such simple methods come up short. Two pairs of monitoring alarm thresholds are shown. For each pair shown, alarms would be generated if observed values either were greater than the upper threshold value or were less than the lower threshold value. The wider green pair of thresholds has the distinct advantage, relative to the narrower red thresholds, of producing false alarms very rarely. This is important, because if false alarms are generated often, either a great deal of time and effort will be wasted responding to them, or costly incidents will go unnoticed, or both. However, as shown in the figure, the wider pair has the distinct disadvantage of being so insensitive to developing costly incidents like the one shown, that by the time an alarm sounds it's too late.

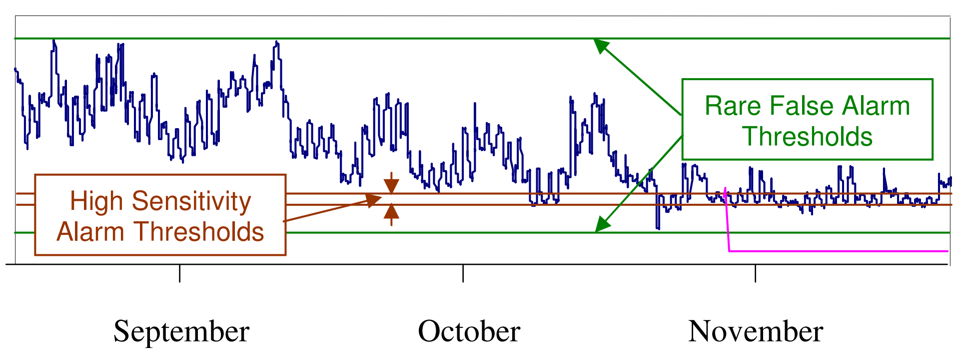

Figure 2. Conventional Alarm Thresholds

The narrow red pair of thresholds shown in Figure 2 has its own key advantage over the wide pair, but also serious disadvantages. If the narrower band were located as shown, it could warn of the incident in the figure in time to prevent it from becoming costly. However, locating the band in the proper position without knowing when the incident is going to begin is not possible. Moreover, even if that problem were solved and the band was located as shown, most of the measured values up to the time of the incident would have been outside the band. As a result many false alarms would have been generated.

Figure 3 illustrates the Brainlike sensing solution. The Brainlike alarm threshold band is very narrow, and it also centered close to actual demand values. Since the band is so narrow, the incident shown can be detected two hours before it becomes costly, allowing enough time to prevent the cause of the incident before it becomes costly. Since the band is centered close to changing demand values, high false alarm rates are eliminated. As a result, Brainlike sensing winds up being far superior to conventional monitoring in this case, in terms of reduced false alarm rates, increased incident sensitivity, and increased incident lead time.

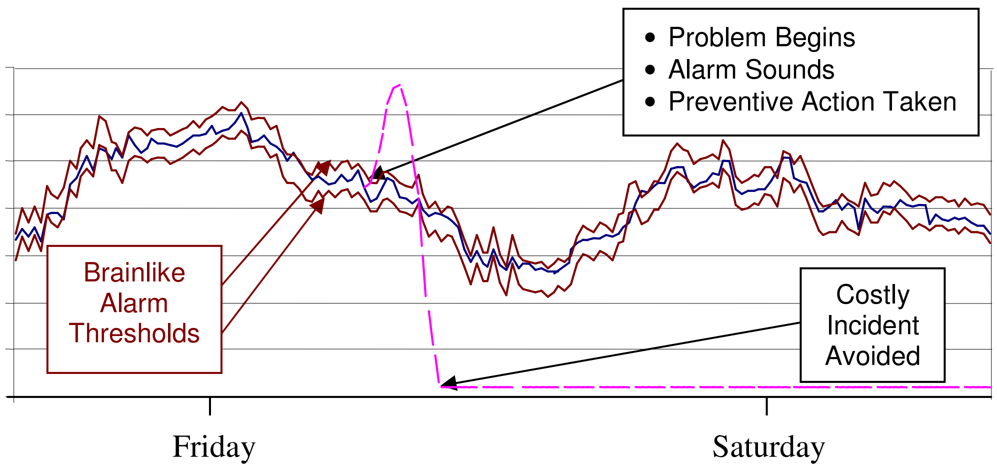

Figure 3. Brainlike Sensing Alarm Thresholds

A detailed treatment of Brainlike sensing technology is provided elsewhere (see Brainlike Enabling Technology Basics), but here is a brief description. Brainlike sensing closely resembles a kind of continuous learning that allows animals to "sniff out" unexpected by continuously and automatically processing multi-sensory information. In the process, they estimate expected values from combined sensor information at each time point. They do this adaptively, automatically, and very precisely.

Once animals have set their expectations for any given sensory channel in this way, they are able to identify unexpected stimuli very quickly and with very high precision. They can also automatically adapt their expectations to changing conditions by continuously learning about changing sensory baselines, as well as changing relationships among sensory channels. In a similar way, Brainlike sensing identifies unexpected incidents with high precision, by continuously and automatically utilizing and learning from multi-sensor information.

Complete automation and highly efficient estimation are key. In principle, sophisticated mathematical models could be developed and implemented that would produce alarm threshold bands like those shown in Figure 3, even without Brainlike sensing. In practice, however, developing and maintaining such models winds up being far too difficult, time consuming, and costly to be generally practical.

Brainlike sensing may not be necessary in applications where measured values are stationary. If instead of the trends shown in Figure 1, baseline data values did not vary over time, they would be relatively simple to monitor. Effective alarm generation rules could be based on having a fixed upper alarm threshold and a fixed lower alarm threshold. Threshold values would be set so that routine variation would produce false alarms at an acceptably rare rate. At the same time, unexpected variation indicative of a developing costly incident would almost always produce valid alarms. Usually, however, even the simplest applications wind up being non-stationary. Traffic patterns change, equipment ages, resource demand develops, and measured values usually differ from one field application to another. As a result, "auto-adaptive" monitoring has much to offer, especially if they can be delivered quickly and affordably.

In summary, Brainlike sensing efficiently improves sensitivity to developing incidents while reducing false alarm rates. The Brainlike advantage comes through continuous, "auto-adaptive" learning of optimal alarm thresholds. Brainlike sensing provides precise, effective surveillance — quickly delivered, easily maintained, and affordably priced.