Steam distribution and energy delivery optimization using wireless sensors

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ABSTRACT

The Extreme Measurement Communications Center at Oak Ridge National Laboratory (ORNL) explores the deployment of a wireless sensor system with a real-time measurement-based energy efficiency optimization framework in the ORNL campus. With particular focus on the 12-mile long steam distribution network in our campus, we propose an integrated system-level approach to optimize the energy delivery within the steam distribution system. We address the goal of achieving significant energy-saving in steam lines by monitoring and acting on leaking steam valves/traps. Our approach leverages an integrated wireless sensor and real-time monitoring capabilities. We make assessments on the real-time status of the distribution system by mounting acoustic sensors on the steam pipes/traps/valves and observe the state measurements of these sensors. Our assessments are based on analysis of the wireless sensor measurements. We describe Fourier-spectrum based algorithms that interpret acoustic vibration sensor data to characterize flows and classify the steam system status. We are able to present the sensor readings, steam flow, steam trap status and the assessed alerts as an interactive overlay within a web-based Google Earth geographic platform that enables decision makers to take remedial action. We believe our demonstration serves as an instantiation of a platform that extends implementation to include newer modalities to manage water flow, sewage and energy consumption.

Keywords: Energy efficiency, steam distribution system, wireless sensor networks, state estimation, steam trap diagnostics, flow rate estimation, spectrogram

1. INTRODUCTION

Steam is one of the principle energy sources for industrial processes used in operations such as process heating, pressure control, mechanical drives, and component separation [1]. In industries that consume large volumes of steam, steam leaks translate to large amounts of wasted energy and money. Our focus in this paper is on the high-volume industrial steam distribution systems that deliver steam from a boiler to the end-use operations. Our aim is to present relatively inexpensive sensor-based methods and analysis algorithms for monitoring and improving the energy efficiency of such steam distribution systems.

In an ideal world, loss-free steam delivery would require perfect piping, insulation, steam traps and condensate recovery systems. But, steam distribution systems are built of components that degrade, and are susceptible to human maintenance errors. Steam distribution systems can suffer losses from less-than-perfect insulation, leaking steam traps, flash steam and dumped condensate. Equipment degradation and energy leaks lead to energy loss that contribute to increased operating costs. In addition, the energy costs accrue over time if maintenance is delayed due to lack of funds or availability of personnel. The delivery loss of an operating steam distribution system can be significantly higher than the expected losses estimated during the system design. For example, in a 150 pound-per-square-inch-gauge (psig) steam system with a production cost of \$4.50 for 1000 pounds of steam, a leak through a hole only 1/32nd of an inch in diameter can increase operating costs by \$185 per year [2].

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A Department of Energy study published in 2004 [3] identified faulty steam traps as a major source of energy waste at industrial sites. The study states that approximately 20% of the steam leaving a central boiler plant is lost via leaking traps in typical space heating systems without proactive assessment programs. In this paper, we present the efforts carried out at Oak Ridge National Laboratory (ORNL) toward exploring the deployment of wireless sensors within a real-time measurement-based energy efficiency optimization framework in the ORNL campus. With particular focus on the steam distribution network, we propose a holistic system-level approach to optimize the energy delivery within the steam distribution system. In particular, we address the goal of saving energy in steam lines by monitoring and acting on leaking steam valves/traps. Our approach is through wireless sensor system integration and real-time monitoring.

We make assessments on the real-time status of the steam distribution system by mounting acoustic sensors on the steam pipes/traps/valves and observe the state measurements of these sensors. Our assessments are based on real-time acoustic algorithms operating on the wireless sensor measurements. We describe two spectral-based approaches acting on the acoustic sensor data to classify the steam traps/valves status and estimate the steam flow in the pipes. The first approach recognizes the status of the steam traps based on frequency domain signatures, while the second approach estimates the steam flow based on the standard deviation of the accelerometer data in frequency and time domains. The analysis based on estimated steam flow and steam trap status helps generate alerts that are presented as an interactive overlay within a web-based Google Earth geographic platform. The visualization of live sensor data enables operators and maintenance personnel to take remedial action. Such an approach is expected to save as much as $675,000 per year on the 12-mile long steam distribution system at ORNL [4].

We have organized the paper to showcase our demonstration as an instantiation of a platform that extends implementation to include newer modalities in managing water flow, sewage, energy consumption that is reproducible in other sites such as in production lines of manufacturing companies. In Section 2, we present the overall system architecture, which includes the backhaul RF network for linking buildings, the steam wireless sensor network, link planning, system design and data flow. In Section 3, the energy signature approach acting on the acoustic vibration sensor data to classify the steam trap status is demonstrated. Section 4 presents our approach for estimating the steam flow from the standard deviation of vibration data. In Section 5, data visualization using a web-based Google Earth geographic platform is presented. We summarize our work and conclude with future directions in Section 6.

2. COMMUNICATION SYSTEM ARCHITECTURE AND INTEGRATION

The wireless communication system architecture is briefly described in this section. To accomplish measurement and other specific tasks associated with energy optimization, ORNL invoked an experimental architecture based on a suite of wireless sensors. Figure 1 describes the system architecture. We began with the construction of a secure wireless backbone providing connectivity for different wireless sensors mounted on pipes and valves spread across the campus. We also considered the future need to accommodate different modalities of sensors (such as temperature, pressure and flow) from different vendors. Different modalities and different vendors implied that we had to acquire data from sensors that may communicate using a diverse array of protocols such as MODBUS [5], OPC [6], and TCP/IP [7]. Our solution to accommodate a variety of sensors and modalities was through the implementation of a middleware layer that understands different protocols. The middleware layer abstracts the vendor-specific protocols and interfaces to the operator. This solution ensures that when we have to add more sensors that adhere to newer/advanced communication protocols, the update to the wireless system only happens at the middleware layer. Another functionality of the middleware is to transform the data into a canonical form for archival in databases. The analysis and visualization components that we present in the later Sections of this paper retrieve data from these databases.

Plan view for the wireless infrastructure created for the pilot project at ORNL is illustrated in Figure 2. There is a central antenna station that houses four sectored antennas to cover different areas of the steam lines along and remote antenna stations for local sensor data aggregation. Extensive consideration was given to cyber-security and site radio-frequency safety requirements. This pilot implementation used the industrial, scientific and medical (ISM) band at 5.8GHz to minimize impacts on the existing Wi-Fi infrastructure. Experiments were conducted to test signal strength and availability across campus to ensure reliable coverage of the wireless infrastructure. The installed communication hardware enables sensor data flows to a centralized location. The centralized server processes the data to identify steam trap status and also estimate flow-rates within the distribution system. We describe the algorithm used for estimating steam trap status in Section 3.

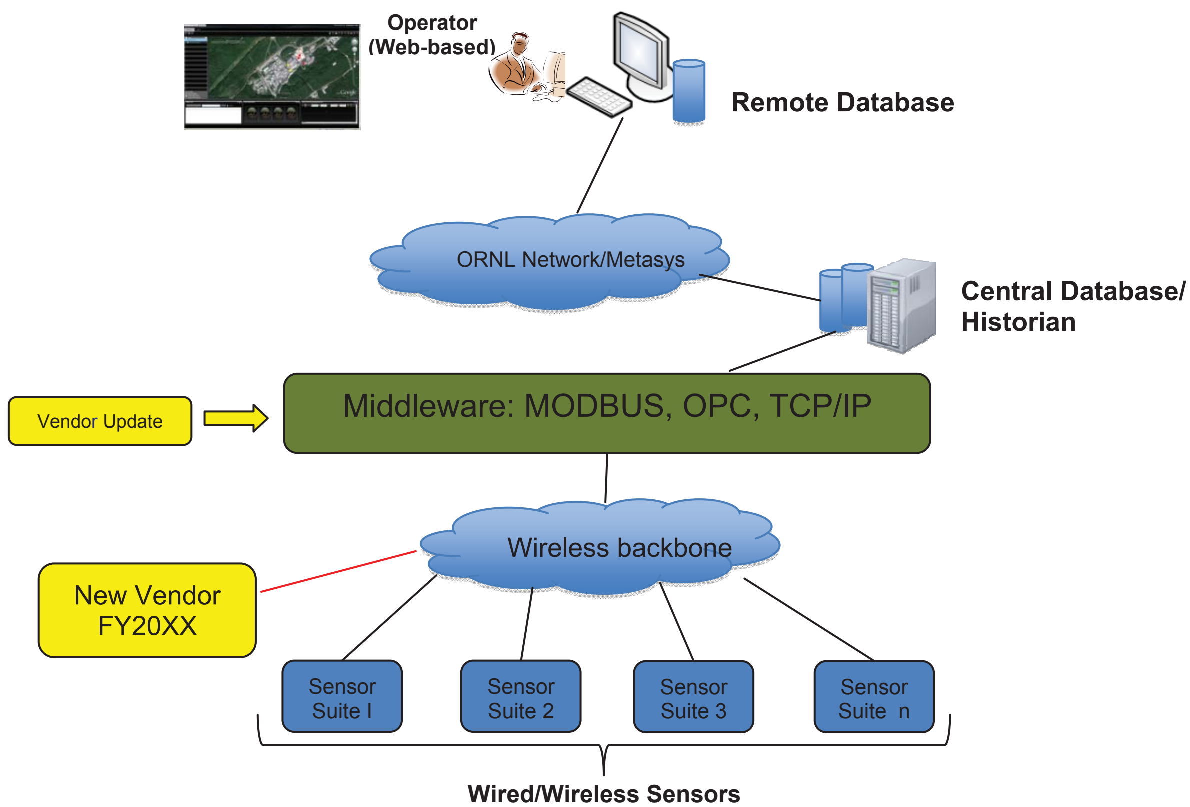


Figure 1. Data-flow architecture of the ORNL wireless energy monitoring system.

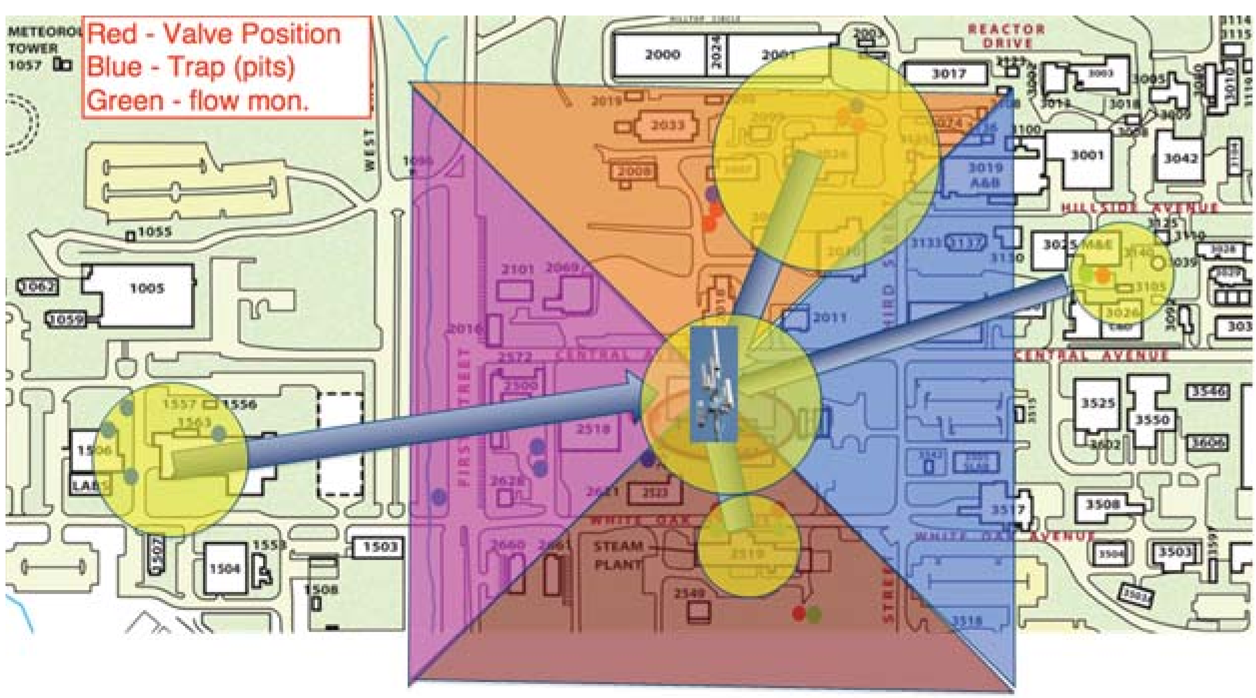


Figure 2. Plan view of ORNL's campus showing the locations of the valves and steam traps in addition to the antenna location and coverage.

3. EXTRACTING SIGNATURES FOR STEAM TRAP STATUS CLASSIFICATION

One of the objectives in this project is to develop a diagnostic capability to assess the operational health of a steam trap. In the event of a failure, we would like to identify the non-operational state with sufficient confidence to enable maintenance decisions to be enforced. This would not only reduce energy losses but also maintenance costs while increasing availability of the system. To achieve this objective, acoustic sensors were strategically placed on or near steam pits to capture operating signatures that help diagnose the health of the steam system.

In the following paragraph, we formulate a spectral-based approach, which can be employed as the diagnostic engine for monitoring steam trap health. The proposed formulation performs energy signature analysis on the time-domain accelerometer measurement data received from the acoustic sensors to identify the various states of their associated steam traps. The first step involves transforming the time-domain accelerometer signal to the frequency-domain by using the short-time Fourier transform, or the spectrogram [8], which is used to compute the time-frequency power spectral density (PSD) [9]. Then, the 2D (time and frequency) PSD is used to compute energy signatures, $\beta_{i,k}$, as described by the following equations:

$$\beta_{i,k} = \int_{f_{i\,lower}}^{f_{i\,upper}} PSD\,(f,k)\ df \tag{1}$$

$$\beta_k = \sqrt{\sum_{i=1}^{I} \beta_{i,k}^2} \tag{2}$$

$$\beta_{Total}(t) = \sum_{k=0}^{t} \beta_k \tag{3}$$

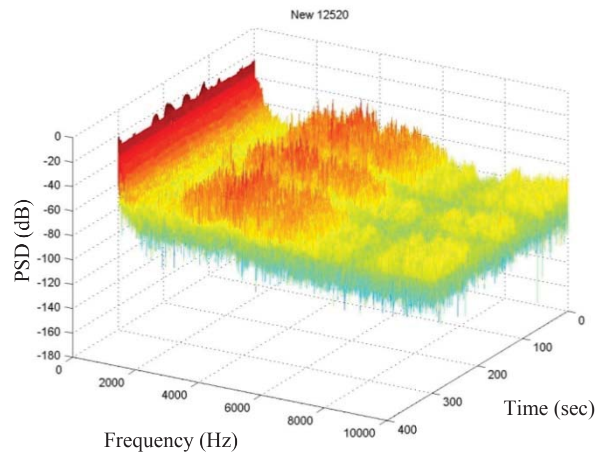
where *PSD* is the time-frequency power spectral density of the received accelerometer data measurements, f is the frequency, k is the discrete-time epochs, f_i's represent the frequency intervals that capture the spectral features, $0 \leq i \leq I$, $0 \leq k \leq K$, $0 \leq t \leq K$, I is the total number of spectral feature sets, and K is the total number of discrete-time epochs.

To identify the $\beta_{i,k}$ of interests and their associated elements, that include f_i's, a complete operational analysis over all ranges of steam trap operations and operational states must be conducted. Such an effort could include a statistical design of experiments approach when all experimental factors and levels cannot be controlled due to operational restrictions. Most steam distribution systems are designed for operator-based flow control. Therefore, for the experiments presented in this paper, we assumed that measurements of all operational states of the distribution system are available. Once all the data is collected, each operational level/state combination is analyzed. We then extract spectral features that will be used in a sensitivity analysis to identify a compact set of $\beta_{i,k}$ to use in the diagnostic algorithm. Given the $\beta_{i,k}$ in equation (1), a vector set of equations (2) and (3) are calculated representing each specific β_k as well as a β_{Total} calculation.

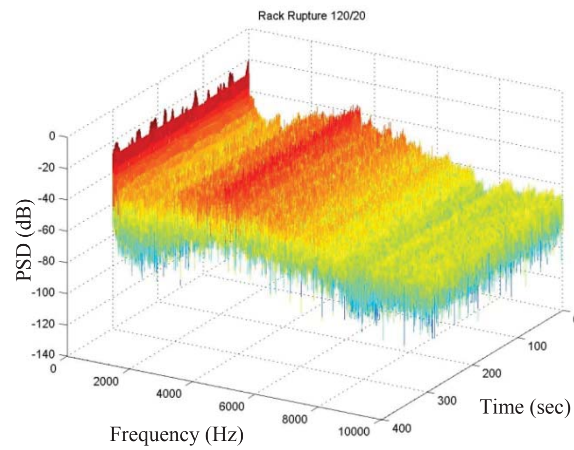
Figure 3 shows the spectral analysis (spectrogram) conducted for a class of steam traps over varying operating ranges and three operational states: (i) New - 125 psi / 20 lbs., (ii) Rupture - 125 psi / 20 lbs. and (iii) Over Press -165 psi / 20 lbs. These results were generated using real accelerometer data sampled at 20 KHz, and each segment (time epoch) in the spectrogram computations is windowed with a Hamming window of length 4096 samples with 50 samples overlap between segments.

Figure 4 shows the overall β_{Total} as a function of discrete time computed by applying equations (1) – (3). Two things are evident from Figure 4. First, the final integrated β_{Total} value for each operational state/condition pairing has sufficient separation in the β_{Total} space to use as a diagnostic indicator. Second, the dynamics exhibited by each operational state/condition pairing β_{Total} over the discrete time of interest is sufficiently different that it would be used as additional support for identifying the steam traps states. Given these energy signatures, β_{Total} in Figure 4, any classification algorithm can be used to identify the state of the steam trap under consideration. Figure 5 shows the final β_{Total} for data sets collected at the input and output of a steam trap that is considered in good state. Notice that the final β_{Total} does not change much when changing the location of the acoustic sensor from the input to the output of the steam trap. Therefore, we conclude that the proposed steam trap health monitoring algorithm is not sensitive to the location of the sensors. This spectral-based approach helps generate alerts based on the estimated signatures from acoustic data.

Another parameter required for ensuring efficient steam delivery is the flow rate. Although a simple solution would be to include flow meters into the steam distribution system, off-the-shelf flow meter installation requires at least a partial stoppage of the distribution line for sensor installation. In the next section, a passive approach to estimation of steam flow from accelerometer data is discussed. Such an approach could reduce the hardware and installation costs required for new flow meters. We also avoid the risk of having to completely or partially sever steam supplies to the industrial operations.



(a)



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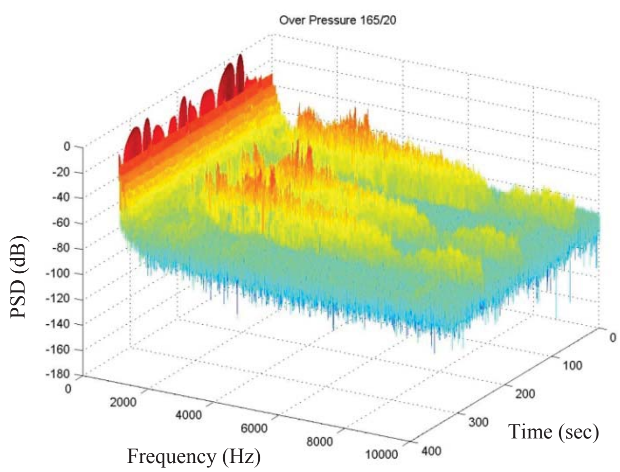

(c)

Figure 3. Time-frequency PSDs of a single class of steam trap types showing varying operational ranges and states, (a) Signatures for New-125 psi / 20 lbs., (b) Signatures for Rupture -125 psi / 20 lbs., and (c) Signatures for Over Press-165 psi / 20 lbs.

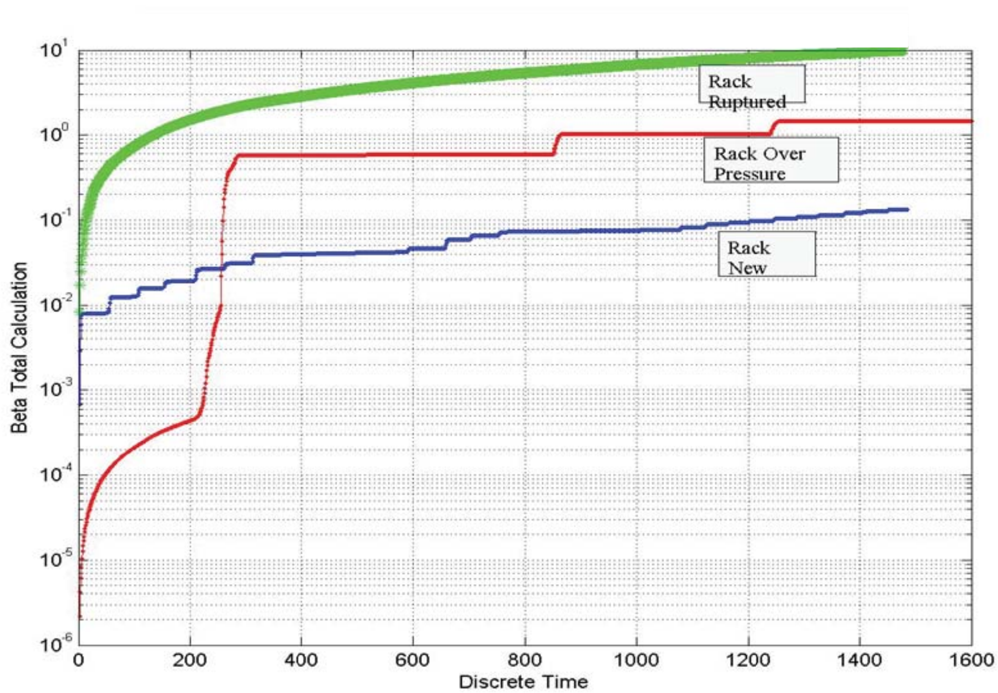

Figure 4. Energy signatures for the three states and health under similar operational conditions (125/165 psi and 20 lbs.).

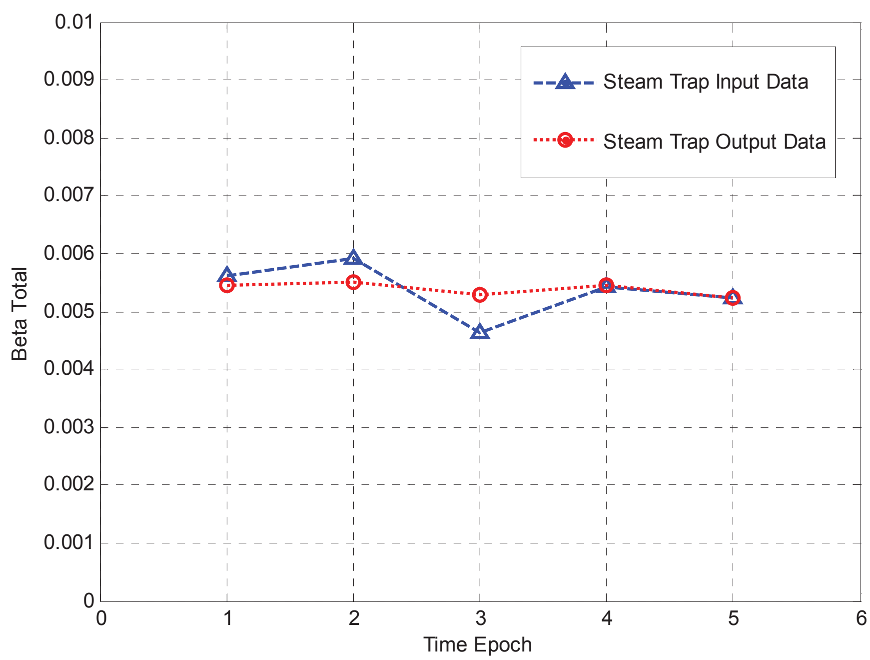

Figure 5. Energy signature values computed on data acquired from the input and output sections of a steam trap. The graph shows that the location of the accelerometer does not influence the prediction of the steam trap status.

4. STEAM FLOW ESTIMATION FROM ACCELEROMETER DATA

In this section, the relationship between flow rate and accelerometer data is investigated. The development of this relationship is inferred from acoustic accelerometer data sampled at 1 KHz and over fixed flow rate periods. We randomly choose 4096 samples at each flow rate. Then, we studied the frequency domain plots of the accelerometer data at different flow rates. These plots reveal interdependencies as shown in Figure 6, for flow rates increasing from 2175 (lit/min) to 2614.06 (lit/min). We are able to observe from Figure 6 that although for the second largest flow rate at 2537.5 and the third largest flow rate at 2482.81 the peaks may not be unique descriptors, the amplitude of the peaks is decreasing with decreasing flow rate. This trend supports our idea that the accelerometer can, indeed, be used to sense changes in the steam-flow.

Next, the relationship between flow-rates and the standard deviation of the accelerometer data in frequency and time domain is derived. The standard deviation of a batch of data can be computed through the following equation:

$$STD = \frac{1}{N-1}\sum_{i=1}^{N}[u_i(t) - \bar{u}]^2 \tag{4}$$

where $u_i(t)$ is the acceleration, N is the total number of acceleration data samples at each flow rate, and $\bar{u}$ is the mean of the data samples which is computed as follows:

$$\bar{u} = \frac{1}{T_1}\int_0^{T_1} u(t)\,dt \tag{5}$$

where T_1 is a time large enough that $\bar{u}$ is the same for any longer time for steady flow.

The relationship between the standard deviation of the acceleration data in time domain and steam flow rate is shown in Figure 7. As seen, the standard deviation is increasing with increasing flow rate from 4.5×10^{-3} to 7×10^{-3}. The solid line represents a second-order least squared error fit to the data. The equation for the curve fit can be expressed as follows:

$$STD_{TD} = 1.35\times10^{-8}r^2 - 5.94\times10^{-5}r + 0.06995 \tag{6}$$

where STD_{TD} is the standard deviation of the acceleration data in time domain and r is the steam flow rate. The relationship between the standard deviation of the acceleration data in frequency domain and steam flow rate is shown in Figure 8. We observe that the standard deviation is increasing with higher flow rates as it increases from 7.2×10^{-5} to 10.7×10^{-5}. As alluded to in the time domain, a quadratic expression similarly exists in the frequency domain. The equation for the curve fit in Figure 8 can be expressed as follows:

$$STD_{FD} = 2.10\times10^{-10}r^2 - 9.27\times10^{-7}r + 0.0011 \tag{7}$$

where STD_{FD} is the standard deviation of the acceleration data in frequency domain. Figures 7 and 8 clearly show that there is a strong correlation between accelerometer data and flow rates and they can be fit by quadratic equations. This agrees with the main conclusion of [10], that sound and vibration signals recorded by the accelerometer mounted to the surface of a pipe has a strong (deterministic) relationship with the flow rate. Based on the real-time flow as recorded by the accelerometers, we can then compute the time or frequency domain statistics and using one of Equations (6) or (7) solve for flow-rate estimates.

Thus far, we presented methods to estimate steam traps/valves status and steam flow rates at control point within the distribution system. In the following section, we present the estimated status and flow rates in addition to raw sensor data as feeds on a web-based interface.

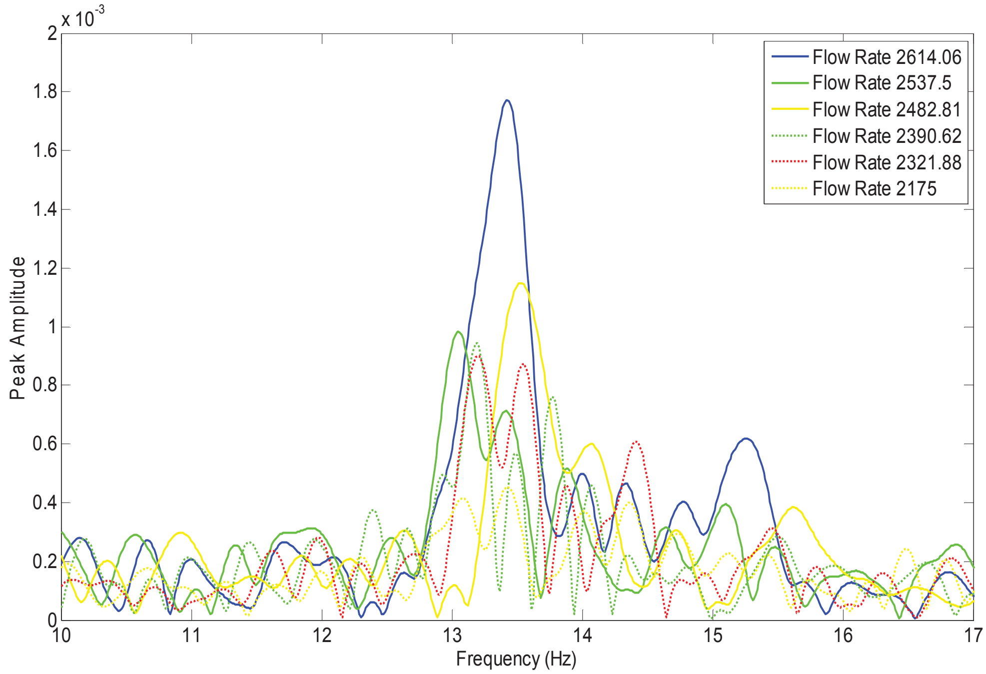

Figure 6. Frequency domain plots (Fourier Transform) of the accelerometer data for different flow rates. These graphs suggest that flow-rates can be assessed based accelerometer measurements.

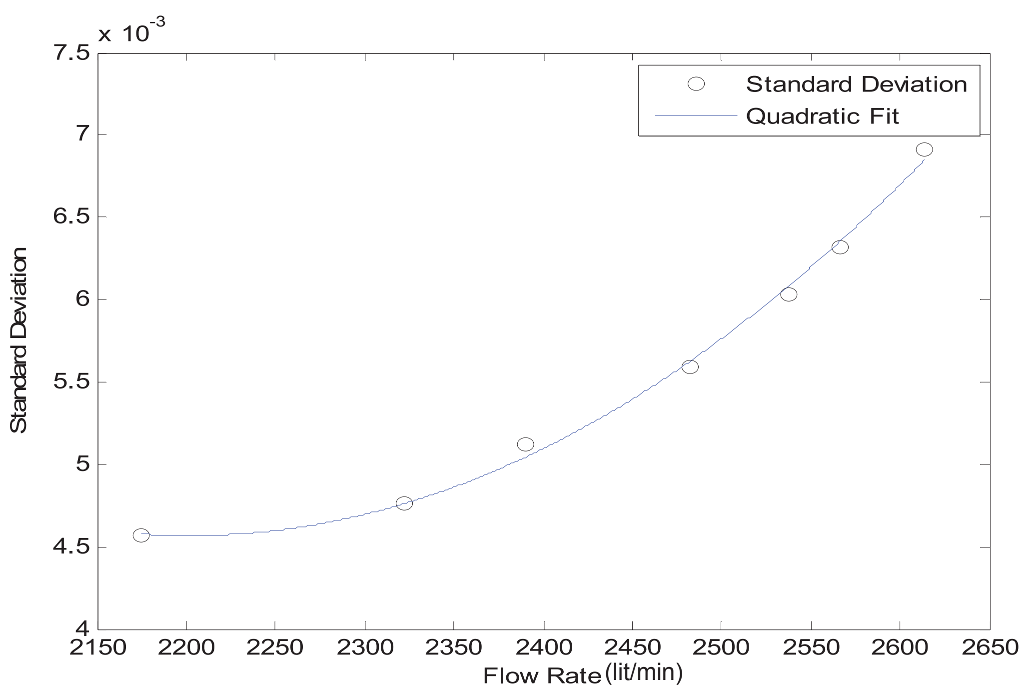

Figure 7. Standard deviation of the time domain accelerometer data appears to have a quadratic relation to the flow rates.

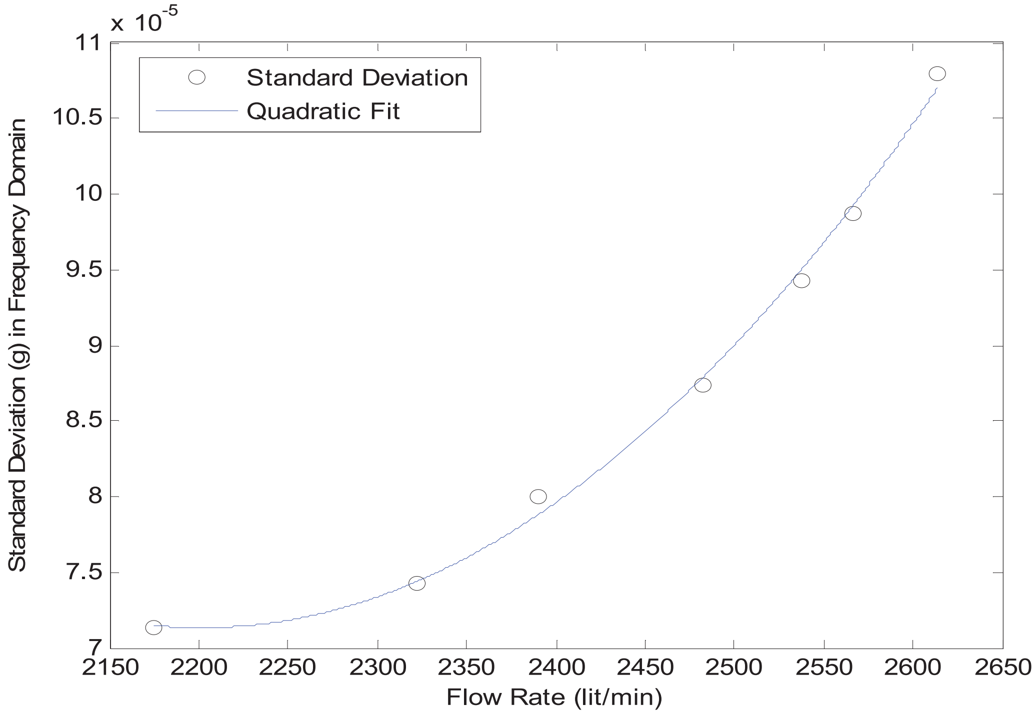

Figure 8. Standard deviation of the accelerometer data in the Fourier domain also appears to have a quadratic relation to the flow rates.

5. VISUALIZATION

As introduced earlier in Figure 1, the wireless sensor data along with the computed estimates of steam trap status and flow rates are brought to a centralized server and archived into a database that can be retrieved upon user request. The data is then made available to operators and maintenance personnel using a browser-based delivery mechanism [11] as shown in Figure 9. The browser based delivery is mobile-phone friendly and very useful for field technicians. Leveraging geo-tagged locations of the steam valves, traps and pipes in the steam distribution system, we are able to deliver sensor data as a Google-Earth [12] overlay.

The green circles on the map in Figure 9 indicate steam valves operating under normal conditions. The red circles indicate potential faults. The radius of the red circles encode the duration for which the potential fault has been identified. Potential faults could be traps failing closed, traps failing open or traps leaking. We use different colors to represent different failure modes. The ability to visualize campus-wide sensor data enables personnel to plan a suitable course of action while maintaining the requirements needed for the industrial operations. The insets below the map, show a table of the most recent measurement values at each of the sensors (bottom far right), measurements of temperature, pressure, flow and battery life as dashboard at a particular building (center) and the list of potential areas of concern within the distribution system (bottom far left). The Google-Earth interface provides an intuitive and interactive mechanism for operators and field technicians to understand the status of the steam distribution system – both during a fault and after a fault has been repaired. We have also implemented the ability to query the history of the steam distribution system from this interface. The slider bar on the top left of the map allows the user to see temporal snapshots of the distribution system. The user-interface design can accommodate a variety of sensors including ones planned in the future for waste management and energy consumption.

Figure 9. The situational awareness interface used to visualize sensor data from the wireless sensors along with status alerts.

6. CONCLUSION

Based on off-the-shelf inexpensive technologies, we proposed the development of a measurement-based energy efficiency optimization framework for a steam distribution system. Two spectral-based algorithms acting on real-time acoustic accelerometer sensor measurements acquired over a wireless network were described. The algorithms identified steam traps status and estimated steam flows in the system. Numerical results show that the energy signature approach has the potential to identify different steam trap states (New, Rupture, and Over Press). We are currently working on capturing the spectral features for other steam trap states such as fail open and fail close, so that they can be identified using the energy signature approach. We also presented a steam flow estimation based on time-domain and/or frequency-domain standard deviation analysis. This method operates on accelerometer measurements collected from acoustic sensors mounted outside steam pipes, and therefore it is an alternative for flow meters that are mounted inside the steam pipes. All readings, charts, and steam traps status are visualized in an interactive overlay within a web-based Google Earth geographic platform. We envision integrating several sensor sources into a unified site-wide monitoring framework. Leveraging the wireless infrastructure, we believe our demonstration serves as an instantiation of a platform that extends implementation to include newer modalities in managing water flow, sewage and energy consumption that is reproducible in other sites such as in production lines of manufacturing companies.

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