Abstract: Recent advances in wireless communication technology and micro electromechanical system have contributed to the development of low-cost, low-power, network-enabled, and multifunctional micro sensors. Due to their ease of deployment, reliability, scalability, flexibility, and self-organization, the existing and potential applications of wireless sensor networks (WSNs) span a wide spectrum in various domains, the environmental and technical requirements of which may differ significantly. The intention of deploying wireless sensors is to gather related information for processing and reporting. In particular, based on data reporting, WSNs can be classified as time-driven, event-driven or data driven. In this paper, a hybrid data-gathering protocol that dynamically switches between the event-driven data-reporting and data-driven data-reporting schemes is proposed. The novel aspect of this approach is that sensor nodes that seem to detect an event of interest in the near future, as well as those nodes detecting the event, become engaged in the adaptive transmission based data-reporting process. This capability enables data from neighboring areas to be gathered proactively without requiring observer intervention. The two algorithms named PED and PAD have the potential to improve the performance of the algorithm in a wireless scenario.
1. Introduction:

Wireless sensors networks are collections of spatially distributed autonomous nodes that are equipped with sensing, computing, and communication abilities. Motivated by military applications such as battlefield surveillance, WSNs are becoming increasingly common, and the existing and potential WSN applications span a wide spectrum in various domains, in which environmental and technical requirements may differ significantly. Examples of representative WSN applications are military applications, environmental monitoring, home and office intelligence and medical care. The purpose of deploying a WSN is to collect relevant data for processing and reporting. In particular, based on data reporting, WSNs can be classified as data-driven, when sensor nodes periodically sense the environment and transmit the data of interest continuously over time, or as event-driven, when sensor nodes react immediately to sudden and drastic changes in the value of a sensed attribute due to the occurrence of a certain event. As communication energy is a major contributor to total energy consumption and is determined by the total communication amount and transmission distance, the data-driven data-reporting scheme may lead to reduced energy consumption and, thus, prolong the network lifetime.

However, as the amount of received data determines the accuracy level, use of the data-driven data-reporting scheme is more appropriate when higher accuracy is required. Therefore, it is essential to make a trade off between accuracy level and resource consumption. In this paper, we propose a hybrid data-gathering protocol that dynamically switches between the event-driven data reporting scheme and the data-driven data-reporting scheme. The proposed protocol behaves as event-driven, meaning that an event of interest triggers data dissemination by sensor nodes. However, from the point at which an event occurs to the point at which the event becomes invalid, the sensor nodes detecting the event continuously send data to an observer, thereby enabling accurate analysis of the environment. The novel aspect of our approach is that not only the sensor nodes that are detecting an event of interest but also those nodes that will potentially detect the event in the near future become engaged in the data-driven data reporting process. This capability enables data from potentially relevant areas to be proactively gathered without requiring observer intervention. As such, the proposed protocol accurately analyzes the environment being monitored using only moderate consumption of valuable resources.
We envision that many real-life WSN applications will benefit from the proposed data-gathering protocol. For instance, consider a human being detection system. As soon as a human entering in the restricted area, it is immediately reported to an observer or reported to the server. Because the Sensor nodes in the restricted area, sense the vibration of the human, so immediately send the vibration data to the observer. In that way this is not only suitable for military application also applicable for navy application also. Similarly, an earthquake detection system is able to gather advance readings of seismic waves produced both at the epicentre and in surrounding areas and quickly raise an alarm for earthquake-prone buildings.

The contributions of this paper are twofold. First, we have developed an adaptive hybrid data-gathering protocol that allows a WSN to dynamically switch between the event-driven data-reporting scheme and the data-driven data reporting scheme based on node context; thus, it is able to more accurately analyze environments than the time-driven data-reporting scheme and use less energy than the time driven data-reporting scheme. Second, we have evaluated the proposed protocol using significant simulation studies. One may argue that a combination of reactive and proactive data-reporting schemes may not be new in the literature. However, the proposed protocol differs from those of previous works in that time and space domain variables are taken into account when a WSN adapts its data-gathering process.

The remainder of this paper is organized as follows Section II summarizes related work, Section III explains the proposed work in detail, Section IV presents the experimental results, and Section V presents the conclusion.

2. Related Work:

Most of the existing data-gathering techniques used in WSNs focus on routing messages in an energy-efficient manner. To minimize energy consumption, routing protocols proposed in the literature for WSNs employ some well-known routing tactics as well as tactics specific to WNSs, e.g., data aggregation and in-network processing, clustering, different node role assignments, and data-centric methods.

A typical WSN consists of hundreds to thousands of sensor nodes deployed over an area; the dense deployment of sensor nodes leads to high correlation of the data sensed by the neighbouring nodes. Hence, the main idea of data aggregation and in-network processing is to combine the data from different nodes reroute by eliminating redundancy, thereby
minimizing the number of transmissions. This process ultimately saves energy and prolongs the network lifetime. Also in the existing method contains the data gathering techniques of time driven and event driven methods. But in this process contain some loss of energy. so in the upcoming method, using instead of time driven data reporting scheme, data driven data reporting scheme used.

Cluster-based routing divides the entire system into distinct clusters, compresses data arriving from nodes that belong to their respective clusters, and sends an aggregated message to the base station. Challenges faced by such a clustering-based approach include how to select the cluster heads and how to organize the clusters. In particular, as it is more likely that cluster heads will drain their batteries faster than cluster members, leading to non uniform depletion of energy in the sensor network, many studies to propose interesting algorithms and mechanisms to handle the different node role assignments.

An important difference between our work and the above-mentioned research is that we focus on dynamic switching between different data-reporting schemes rather than energy-efficient data dissemination for a given data-reporting scheme in WSNs. Therefore, our work can be further enhanced by the use of existing power-aware routing protocols. So in this project does not use the time driven data reporting scheme. For instance, data aggregation and in-network process can significantly reduce energy consumption, particularly when many sensor nodes use a data driven data-reporting scheme.

With regard to the dynamic switching of data-reporting schemes, APTEEN and SINA are previous studies that are closely related to the current research. APTEEN uses a hard and a soft threshold that allow sensor nodes to transmit data only when the sensed attributes within the range of interest. It also parameterizes the maximum time period between two successive reports sent by a sensor node (i.e., count time) so that the node is forced to transmit sensed data if it has not done so for a long period of time. As such, APTEEN combines reactive and proactive data-reporting schemes. However, in APTEEN, only a parameter in the time domain determines when proactive data-reporting schemes used. As a consequence, every sensor node in the network participate sina proactive data-reporting process regardless of its relevance to an event of interest. On the other hand, our approach considers variables in the space and time domains to make such decisions. In doing so, sensor nodes that detect an event of interest or those nodes that are likely to detect the event in the near future become engaged in a proactive data-reporting process. This capability can significantly eliminate
unnecessary data dissemination from sensor nodes that are irrelevant to the event. The solution of this method, Nodes that detect an event of interest or those nodes that are likely to detect the event in the near future become engaged in a proactive data reporting through spatio-temporal correlation of data.

SINA selects the most appropriate data distribution and collection method based on the nature of the queries and the current network status. Specifically, individual sensor nodes make autonomous decisions about whether they should participate in the information-gathering process based on the probability of a given response. Furthermore, sensor nodes are able to defer sending data for a period of time. These methods maximize the response quality in terms of number and responsiveness while minimizing network resource consumption. Although SINA selectively includes the sensor nodes to gather the data, as in our approach, the considered application models differ. In addition, SINA does not support dynamic switching between data-reporting schemes. The solution of this method, Dynamic switching enables context aware energy saving.

3. Proposed Work:

The features of the hybrid data-gathering protocol proposed in this paper are: 1) it switches dynamically between the event-driven and the data-driven data-reporting scheme, and 2) sensor nodes will detect the events in the near future, and also engaged in the data-driven data-reporting process. Under normal conditions, sensor Nodes responds only when the vibration is above threshold value. When the sensor nodes realize that the abnormal condition is not transient they switch off the data-driven data-reporting scheme and continuously broadcast the vibration data to an observer. Furthermore, they notify other nodes of their changes so that neighbouring nodes continuously broadcast data as well. The nodes switch back to the event-driven data reporting scheme, when the vibration goes below threshold value.

In order to determine the switching between the two data-reporting schemes and the sensor nodes that will detect the events in the near future, which typically are in close proximity to those nodes detecting the events? To fulfill these requirements, there must be a mechanism to determine in an event manner when to switch between the two data-reporting schemes and which sensor nodes to involve in the event-driven data-reporting process. Depending on these
answers, several policies can exist. In this paper, we present two algorithms: the parameter-based event detection (PED) algorithm and the parameter-based are a detection (PAD) algorithm.

4. Algorithm:

Step 1: Set the threshold value \( \alpha \), Initialize the current and previous threshold values over the corresponding time intervals \((S_{curr}, S_{prev})\)

Step 2: Choose the mode of operation (event or data driven)

For Event driven:

Step 3: If the threshold variable over current time window is greater than or equal to \( \alpha \) and previous value counter variables \( p \& q \) are incremented by one, or If \( S_{curr} \) is greater than or equal to \( \alpha \) and less than previous value then only \( q \) is incremented by one.

Step 4: Otherwise initialize the counter values \( p \& q \) as zero.

Step 5: If both the counter variables are greater than starting values of their corresponding values then switch to “data driven mode”.

For Data driven:

Step 3: If the threshold variable over current time window is less than \( \alpha \) and previous value counter variables \( p \& q \) are incremented by one, or if \( S_{curr} \) is less than \( \alpha \) and less than previous value then only \( q \) is incremented by one.

Step 4: Otherwise initialize the counter values \( p \& q \) as zero.

Step 5: If both the counter variables are greater than stop values of their corresponding values then switch to “Event driven mode”.
4.1. PED Algorithm:

The PED algorithm in Fig. 1 is given a threshold vale and two pairs of parameters controlling the level of aggressiveness for changes in data dissemination schemes. When the cluster numbers are the sensor nodes that actually sense the physical conditions, the threshold value determines what percentage of sensor nodes within the same cluster detects the event. Otherwise the percentage of lower level clusters reporting in a continues manner is used for the threshold value. Each pair of parameter (Pstart, Qstart) and (Pstop, Qstop), is used to determine when to start or stop the continuous data dissemination, respectively. Start denotes maximum number of time intervals with an increasing slop of the threshold variable, and Qstart denotes the maximum number of time interval that the threshold is exceeded, regardless of the slope. Similarly, when Pstart and Qstart are used a decreasing slop of the threshold variable and the time intervals that do not exceed the threshold variable are applied respectively.

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**Figure 1: Proposed algorithm.**
4.2. PAD Algorithm:

Once a sensor node decided to switch the data dissemination scheme the next decision to make is which sensor node must be affected by that decision in our approach the pad algorithm deals with the cluster members as a whole. In other words when the data dissemination scheme is selects by a cluster head then all of the sensor nodes within the cluster will be directed to report data in that manner. Our simple approach is based on the argument that the closer a sensor node is located to the sensor nodes that detect an event ,the more likely it I that the sensor node is relevant to that event in the near future, as clusters are typically form according to proximity. For instance the current temperature measured by sensor nodes located close to the fire , say may not be high enough to trigger an event but would be much higher than those of nodes tens of miles away from the fire therefore the possibility that those sensor nodes soon trigger the event becomes high. But this approach may not work very well in some cases for instance if sensor nodes detecting an event are located at the border between cluster those nodes in other clusters can be included only when enough clusters at the same level have initiated continuous data dissemination.

Once a sensor node switches to the event-driven data reporting scheme, it broadcasts its change to engage neighbouring sensor nodes in the continuous data dissemination. The range of the neighbourhood is determined by the PAD algorithm, which is based on two configurable parameters: time-to-live (TTL) and valid time (VT). TTL represents the number of hops within which sensor nodes must switch to the time driven data-reporting scheme. The use of TTL in the PAD algorithm is similar to that in computer network technology, where TTL specifies the number of hops that a message can travel to before it should be discarded. When a sensor node receives a broadcast message containing a TTL value that is greater than
zero, it switches to the time-driven data-reporting scheme and rebroadcasts a TTL value decremented by one. This process continues until the TTL value becomes zero. This approach is based on the argument that the nearer a sensor node is located to the sensor nodes that detect an event, the more likely it is that the sensor node will be relevant to that event in the near future since sensor nodes are formed according to proximity. For instance, the current temperature measured by sensor nodes located close to the fire may not be high enough to trigger an event, but it would be much higher than those of nodes tens of miles away from the fire. Therefore, the possibility that the closely located sensor nodes will detect an event in the near future increases. VT is the other important parameter of the PAD algorithm, and it specifies how long a sensor node should use the time-driven data-reporting scheme regardless of the result of its PED algorithm. Note that VT is used only for those sensor nodes that are switched to the time-driven data-reporting scheme by TTL. The necessity of VT arises from the fact that sensor nodes in the vicinity of the area where an event occurs may not yet detect the event. Therefore, without VT, they could immediately switch back to the event-driven data reporting scheme, losing the chance to acquire important information in advance.

![Illustration of TTL propagation.](image)

This approach behaves well in multiple event-detection environments, in which sensor nodes are capable of sensing different attributes through simple modification of the PAD algorithm. For instance, a sensor node executes the PED algorithm for each sensed attribute and broadcasts its switching to the data-driven data reporting scheme to neighbouring nodes accordingly. By sending not only TTL and VT but also the type of attribute that caused the switching, the sensor node allows neighbouring nodes to determine what type of data they need to collect in a data-driven manner.
5. Experimental Results:

The simulator can operate in either the deterministic mode to produce replicable results while testing an application or in the probabilistic mode to simulate the non-deterministic nature of the communication channel and the low-level communication protocol of the sensor nodes.

The following table shows the power consumption parameter of some common radios which are being used frequently and some off-the-shelf sensors.

<table>
<thead>
<tr>
<th>Radio</th>
<th>Producer</th>
<th>Power Consumption</th>
<th>Transmission</th>
<th>Reception</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC2420</td>
<td>Texas Instruments</td>
<td>35 mW (at 0 dBm)</td>
<td>38 mW</td>
<td></td>
</tr>
<tr>
<td>CC1000</td>
<td>Texas Instruments</td>
<td>42 mW (at 0 dBm)</td>
<td>29 mW</td>
<td></td>
</tr>
<tr>
<td>TR1000</td>
<td>RF Monolithics</td>
<td>36 mW (at 0 dBm)</td>
<td>9 mW</td>
<td></td>
</tr>
</tbody>
</table>

**Table 1**

The simulation was performed on a network of 1000 sensor nodes and a fixed base station. The nodes were placed randomly in the network, and it was assumed that they do not change position.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Producer</th>
<th>Sensing</th>
<th>Power Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>STC75</td>
<td>STEM</td>
<td>Temperature</td>
<td>0.4 mW</td>
</tr>
<tr>
<td>QST108K16</td>
<td>STEM</td>
<td>Touch</td>
<td>7 mW</td>
</tr>
<tr>
<td>SG-LINK (1000G)</td>
<td>MicroStrain</td>
<td>Strain gauge</td>
<td>9 mW</td>
</tr>
<tr>
<td>SRM3S</td>
<td>AED</td>
<td>Accelerometer (1 m/s)</td>
<td>30 mW</td>
</tr>
<tr>
<td>2200 Series, 2600 Series</td>
<td>CSI</td>
<td>Pressure</td>
<td>50 mW</td>
</tr>
<tr>
<td>T150</td>
<td>GEFRAN</td>
<td>Humidity</td>
<td>90 mW</td>
</tr>
<tr>
<td>LCC-A10</td>
<td>PEPPERI - FUCHS</td>
<td>Level Sensor</td>
<td>300 mW</td>
</tr>
<tr>
<td>TDA0104</td>
<td>STMicro</td>
<td>Proximity</td>
<td>420 mW</td>
</tr>
<tr>
<td>TCS+GL2A4+APBX4H11141</td>
<td>TURCK</td>
<td>Flow Control</td>
<td>1250 mW</td>
</tr>
</tbody>
</table>

**Table 2**
Figure 4: This graph represents the power consumption between data and event driven methods.

Figure 5: Performance comparison of different algorithm.

This figure represents the sensor nodes in event driven and data driven. Here set the port is com1. After occurring the event, the event driven changed from the event driven to data driven. So in the parameter based area detection is used for choosing the area, in where the event was occurred.
The below graph indicates the power loss between time driven and data driven.

![Graph showing power loss comparison]

**Figure 7: Power Loss Differences**

In this table, shows the values of power loss comparison between data driven and time driven.
Table 3: Values in Power Losses

<table>
<thead>
<tr>
<th>No of transmissions</th>
<th>Power loss in mw</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Time driven</td>
<td>Data driven</td>
</tr>
<tr>
<td>1322</td>
<td>87</td>
</tr>
<tr>
<td>677</td>
<td>45</td>
</tr>
<tr>
<td>2555</td>
<td>169</td>
</tr>
</tbody>
</table>

6. Conclusion:

In this paper, we proposed a hybrid data-gathering protocol that dynamically switches between the data-driven data-reporting scheme and the event-driven data-reporting scheme. The essential elements of the protocol were that: 1) it switches between two data-reporting schemes to acquire as much information as possible while consuming only moderate amounts of energy and 2) it allows sensor nodes in close proximity to those nodes detecting an event to be proactively engaged in continuous data dissemination, thus enabling accurate analysis of future behaviours of the environment being monitored. To fulfil these requirements, there must be a mechanism to determine in a timely manner when to switch between the data-reporting schemes, and which sensor nodes to involve in the data-driven data-reporting process. To address these problems, we presented the PED and the PAD algorithms, and showed the effectiveness so four approach via a simulation study.

Future work lies in several areas. As the experimental results showed, the behaviours of the hybrid data-gathering protocol depend on the configurable parameters. One of our future researches objectivises to develop algorithms for the dynamic selection of configurable parameters based on the characteristics of the target environment. In addition, the PAD algorithm considers only closeness to the target area, which is defined by the number of hops. This information may include irrelevant sensor nodes such as those in the areas that are
coming to a state of lull. Therefore, future work should extend the PAD algorithm to incorporate the contextual information of sensor nodes.
References: