Adaptive Correctness Monitoring for Wireless Sensor Networks Using Hierarchical Distributed Run-Time Invariant Checking

DOUGLAS HERBERT, VINAITHEERTHAN SUNDARAM, YUNG-HSIANG LU, SAURABH BAGCHI, and ZHIYUAN LI
Purdue University

This article presents a hierarchical approach for detecting faults in wireless sensor networks (WSNs) after they have been deployed. The developers of WSNs can specify "invariants" that must be satisfied by the WSNs. We present a framework, Hierarchical SEnsor Network Debugging (H-SEND), for lightweight checking of invariants. H-SEND is able to detect a large class of faults in data-gathering WSNs, and leverages the existing message flow in the network by buffering and piggybacking messages. H-SEND checks as closely to the source of a fault as possible, pinpointing the fault quickly and efficiently in terms of additional network traffic. Therefore, H-SEND is suited to bandwidth or communication energy constrained networks. A specification expression is provided for specifying invariants so that a protocol developer can write behavioral level invariants. We hypothesize that data from sensor nodes does not change dramatically, but rather changes gradually over time. We extend our framework for the invariants that includes values determined at run-time in order to detect data trends. The value range can be based on information local to a single node or the surrounding nodes' values. Using our system, developers can write invariants to detect data trends without prior knowledge of correct values. Automatic value detection can be used to detect anomalies that cannot be detected in existing WSNs. To demonstrate the benefits of run-time range detection and fault checking, we construct a prototype WSN using CO_2 and temperature sensors coupled to Mica2 motes. We show that our method can detect sudden changes of the environments with little overhead in communication, computation, and storage.

This article is based on the paper "Detection and Repair of Software Errors in Hierarchical Sensor Networks" by Douglas Herbert, Yung-Hsiang Lu, Saurabh Bagchi, and Zhiyuan Li, which appears in the Proceedings of the IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing, 403–410. © 2006 IEEE.
Doug Herbert was supported by the Tellabs Fellowship from Purdue's Center for Wireless Systems and Applications. This project is supported in part by the National Science Foundation grant CNS 0509394 and by Purdue Research Foundation. Any opinions, findings, and conclusions or recommendations in the projects are those of the authors and do not necessarily reflect the views of the sponsors.
Authors' address: School of Electrical and Computer Engineering, Department of Computer Science, Purdue University, West Lafayette, IN 47907; email: {herbertd, vsundar, yunglu, and sbagchi}@purdue.edu; li@cs.purdue.edu.

Categories and Subject Descriptors: C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Distributed networks, network communications, packet-switching networks*

General Terms: Reliability, Verification, Design

Additional Key Words and Phrases: Invariants, correctness monitoring, run-time, tools, fault tolerance and diagnostics, in-network processing and aggregation, network protocols, programming models and languages, data integrity

ACM Reference Format:

Herbert, D., Sundaram, V., Lu, Y.-H., Bagchi, S., and Li, Z. 2007. Adaptive correctness monitoring for wireless sensor networks using hierarchical distributed run-time invariant checking. ACM Trans. Autonom. Adapt. Syst. 2, 3, Article 8 (September 2007), 23 pages. DOI = 10.1145/1278460.1278462 http://doi.acm.org/10.1145/1278460.1278462

1. INTRODUCTION

Wireless Sensor Networks (WSNs) enable continuous data collection or rare event detection in large, hazardous or remote areas. The data being collected can be critical. Detecting indoor air quality or tracking tank movement are two examples from civilian and military domains. WSNs are comprised of many sensors that may fail for many reasons. Faults may come from incorrect sensor network protocols. Distributed protocols are widely recognized as being difficult to design [Tel 1991]. WSNs present unique challenges because of the lack of sophisticated debugging tools and the difficulty of testing after deployment. Even after extensive testing, faults may still occur due to environment conditions, such as high temperatures. While this is true of many systems, this is especially true with WSNs as they are *in situ* in physical environments that may be changing over the period of deployment. Regardless of design or validation, sensors can still be damaged by unexpected factors such as storms, hail, animals, or flood.

Run-time techniques can detect faults in order to maintain high-fidelity data in the presence of possible faults from design, implementation, or a hostile environment. Earlier work for run-time observation in wired networks [Diaz et al. 1994; Khanna et al. 2004; Zulkernine and Seviora 2002] does not directly apply to WSNs as they are resource-limited. It is essential to minimize the overhead of storage, computation, and communication in observation and detection. We developed a framework called Hierarchical SEnsor Network Debugging (H-SEND) [Herbert et al. 2006] to observe node conditions and network traffic for detecting symptoms of faults. H-SEND differs from existing work in that it is specialized for large scale WSNs. H-SEND has four key steps: (a) During program development, a programmer can specify important properties as "invariants" that should never be violated in the network's operation. (b) When the program is compiled, the code for checking invariants is automatically inserted. An invariant may be checked locally by an individual node or remotely by sending messages to another node for detecting faults that cannot be determined by a single sensor node. (c) After deployment, the inserted code is used to detect abnormal behavior of the network. An anomaly is detected when an invariant is violated. An invariant may include a fixed value determined at compile time, or a data trend observed at run time. Once detected, an anomaly can trigger several actions, such as increasing logging details or reporting faults to the base station. (d) After a fault is detected, it is reported to the programmer and a new program is uploaded to the relevant nodes through multi-hop wireless reprogramming. H-SEND is designed for WSNs with the following special consideration:

(a) Our approach has small overhead in storage, computation, and communication. H-SEND checks invariants through a hierarchy without sending all observed variables to a central location for detection. Instead, invariants are checked at the closest nodes where the requisite information is available. We present the analysis of the overhead in Section 4.4.
(b) H-SEND assists programmers by automatically (or semi-automatically) determining where to insert invariant checking code and when to send messages that include observed variables. A programmer only needs to specify the invariants and the variables to be observed. Our tool can determine the locations to insert code for checking invariants and to send observed information.
(c) Using H-SEND, faults may be detected by comparing the values from multiple nodes. H-SEND can observe data trends that are determined only at run-time, such as temperature changes in a wildlife preserve. In normal operations, temperatures do not change suddenly. A sudden rise of temperature may be caused by fire and must be reported immediately. We can compare current values against historical values on an individual node (temporal trend) or the current values on surrounding nodes (spatial trend).
(d) H-SEND can handle WSNs with heterogeneous nodes that are organized as hierarchies. Different nodes may check different types of invariants and also perform remote checking when observed information is aggregated.

We construct a prototype WSN to demonstrate H-SEND through a leader election and data gathering protocol in a hierarchical configuration. Some invariants are local to a node but others are collective to a cluster or the entire network. We choose a representative leader election protocol called LEACH (Low-Energy Adaptive Clustering Hierarchy) Heinzelman et al. [2000, 2002]. LEACH assigns cluster heads in a near round-robin manner to evenly distribute energy drain. A set of invariants is inserted into the application code. We detect both temporal and spatial trends based on data collected from our CO_2 and temperature sensors coupled to Mica2 motes with custom built power supply and interface circuits. Figure 1 shows the measurement of CO_2 in a campus lounge where some students find an ideal place to nap. Learning would suffer if the level of CO_2 in a classroom was this high. This indicates the necessity of monitoring CO_2 level in indoor environments. Our method can detect sudden CO_2 level increases, such as at the start of a class, triggering an invariant violation which can increase air flow to the room. We use simulations to measure the overhead of invariant augmented code in our approach. The experiments and simulations show that data trends can be observed and used to detect anomalies with small overhead.

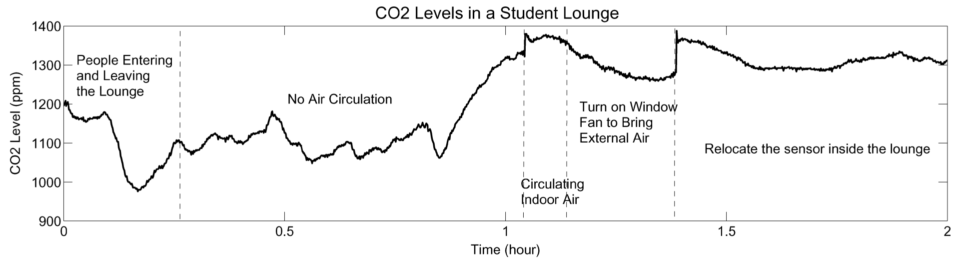


Fig. 1. CO_2 levels observed in multiple locations in student lounge.

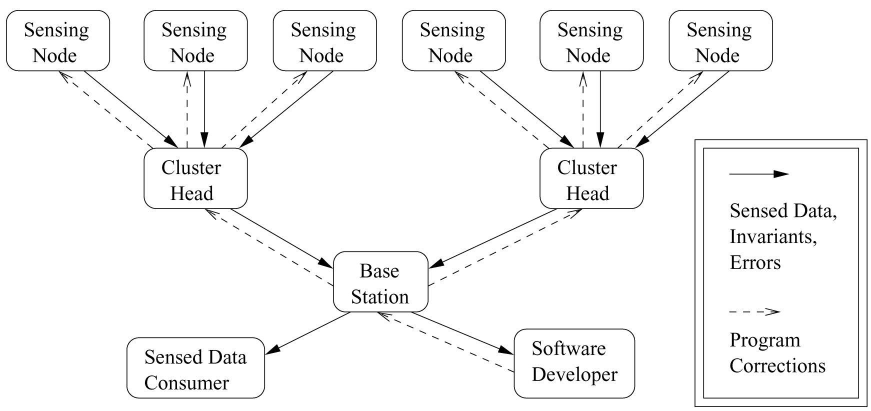


Fig. 2. Overview of the framework for fault detection, propagation, diagnosis, and repair.

2. RELATED WORK

2.1 Sensor Programming Environment and Simulation

A typical hierarchical sensor network is shown in Figure 2. Once sensor network software is created by a developer, it may be uploaded to individual sensors by utilizing distributed propagation techniques over a radio link [Hui and Culler 2004] as illustrated in Figure 2. Berkeley Mica Motes [Hill and Culler 2002] are widely used sensor nodes for experiments. Mica nodes use TinyOS as the run-time environment. TinyOS provides an event-based simulator, TOSSIM, which can be used to simulate a network of varying node sizes [Levis et al. 2003]. TOSSIM compiles from the same source code as the Mica platform. Our experiments use TOSSIM because it easily scales to large numbers of nodes. TOSSIM provides deterministic results so it is a better test bed in contrast to the nondeterministic results provided by real-life execution. Finally, TOSSIM allows us to separate instrumentation code from the actual code running on each node so we can measure the nodes' behavior without perturbing the network's normal operations. To increase the accuracy of our simulation, we inject sensed values from actual sensors, and use these values to simulate data collection.

2.2 Program Monitoring and Profiling

Program monitoring and profiling have been developed for wired networks [Diaz et al. 1994; Khanna et al. 2004; Zulkernine and Seviora 2002]. One approach is to directly modify binary code [Kumar et al. 2005] using binary analysis tools to insert instrumentation code to monitor program operation. This approach detects faults in programs while operating in a real environment. DIDUCE [Hangal and Lam 2002] instruments source code and formulates hypotheses of possible rules about correct program operations. DIDUCE uses machine learning by starting with strict rules that are gradually relaxed to allow new program behavior. Formal methods have been used to prove program's behavior from a theoretical view [Hamlet 2005]. Analysis of program operations with an SQL-like language is used for correctness monitoring in [Goldsmith et al. 2005]. Adding hardware to monitor memory changes for checking at run-time is discussed in [Zhou et al. 2005; Wang et al. 2006]. Several studies discuss how to find invariants for programs [Perkins and Ernst 2004; Ernst et al. 2001; Yen et al. 2001]. These studies provide the foundation for using invariants in WSNs, but existing approaches cannot be directly applied to WSNs because the observation algorithms may execute at a location far away from nodes where data are collected, adding significant network traffic to propagate data. Since WSNs are resource-limited, invariant checking must be efficient in using the sensor nodes' communication and computation.

2.3 Clustering

WSNs are distributed systems. Distributed algorithms have been studied in [Lynch 1996]. WSNs differ from wired distributed systems because sensors have stringent resource constraints, including energy, storage, and computation capability. To conserve energy, some routing protocols use hierarchies among sensor nodes [Soro and Heinzelman 2005; Younis et al. 2002], preventing all nodes from relaying all messages (routing by "flooding"). Sensor nodes are often divided into clusters and a special node or "cluster head" (CH) in each cluster relays messages between clusters or to a base station. Cluster heads can be chosen in several ways. If sensor nodes are heterogeneous, the nodes that have more resources are selected as cluster heads. For homogeneous nodes, they can take turns playing the role of the cluster head through leader election protocols [Dolev et al. 1997; Nakano and Olariu 2002; Singh 1996].

2.4 Fault Detection and Recovery

Studies have been conducted to observe run-time behavior for wired networks [Diaz et al. 1994; Khanna et al. 2004; Zulkernine and Seviora 2002]. In these studies, the observed node and the observer are different so this approach provides several advantages: (a) An observer may be a monolithic entity with perfect knowledge of the observed node. (b) An observer may be fault-proof or may only fail in constrained ways, such as fail-silence. (c) An observer may have abundant resources. Fault observation in resource-constrained WSNs has also been studied. Several projects use local observation whereby nodes oversee traffic passing through the neighbor nodes [Nasipuri et al. 2001; Pirzada and McDonald 2004; Marti et al. 2000; Buchegger and Boudec 2002; an Huang and Lee 2003; Khalil et al. 2005, 2006]. Each node can both sense the environment and observe other nodes. Previous work uses local observation to build trust relationships among nodes in networks [Buchegger and Boudec 2002; Pirzada and McDonald 2004], detect attacks [Marti et al. 2000; an Huang and Lee 2003], or discover routes with certain properties, such as a node becoming disconnected [Nasipuri et al. 2001]. an Huang et al. [2003] propose distributed intrusion observation for ad hoc networks. Their paper uses machine learning to choose the parameters needed to accurately detect faults. Intrusion detection systems exist [Vigna et al. 2004; Medidi et al. 2003]. However, the knowledge in these systems is built by each individual node without the need for coordination, and no information is transmitted to remote nodes. Smith et al. [1997] detect protocol faults for ad hoc networks. After faults are detected, new programs may be sent to the sensor nodes through the same wireless network for transmitting data. Deluge [Hui and Culler 2004] allows program replacement by propagating new program images over wireless networks. In our previous work [Khalil et al. 2005], we presented a method to enable neighbor observation in resource-constrained environments and to provide the structures and the state to be maintained at each node. We analyze the capabilities and the limitations of local observation for WSNs.

2.5 Estimation and Approximate Agreement

A summary of approximate agreement upon a single value is provided by Lynch [1996]. Lamport et al. [1982] formulate the Byzantine Generals problem of gaining distributed consensus in the presence of faults. It is shown that for $3N + 1$ nodes reporting binary (true or false) data, the correct value can be determined if no more than N nodes report incorrect values. Maheney et al. [1985] show that continuous value estimation requires fewer correct nodes to achieve consensus for a given degree of fault tolerance. Two-thirds of nodes performing correctly guarantee convergence of their algorithm. If between one-third and two-thirds of nodes perform correctly, their algorithm can detect that too many faults have occurred to determine correctness or show that the divergence is bounded. Marzullo [1990] provides an algorithm to obtain inexact agreement for continuously valued data, and presents a method of transforming a process control program for better fault tolerance. Marzullo demonstrates how to modify specifications to accommodate uncertainty.

2.6 Benefits of CO_2 Monitoring

Many studies have provided the relationship between the concentration of carbon dioxide (CO_2) and indoor air quality [Seppanen et al. 1999; Erdmann et al. 2002; Milton et al. 2000]. In an office building, occupants (people) are the primary source of CO_2. High levels of CO_2 (usually above 1000 parts per million, or ppm) are connected with sick building syndrome (SBS) symptoms. As a reference, the CO_2 level in outdoor air is usually below 350 ppm. Even though CO_2 levels are not a direct indicator of indoor air quality, the CO_2 levels can provide indirect information of ventilation efficiency, SBS, respiratory disease,

Fig. 3. Device for measuring airflow volume.

and occupant absence. Every year, approximately 4 million deaths occur due to viral respiratory infections [Liao et al. 2005]. Liao et al. [2005] develop a model for the infection of influenza and severe acute respiratory syndrome (SARS) for indoor environment. Studies show that increasing ventilation can reduce the infection of airborne diseases [Yu et al. 2004; Liao et al. 2005; Myatt et al. 2004; Rudnick and Milton 2003]. Ventilation volume for uninstrumented spaces is commonly collected with a device that fits over the supply vent, and forces air to flow through the measurement device, as shown in Figure 3. This method measures only one data point. We use multiple CO_2 sensors as indicators of ventilation volume, and transmit sensor readings to a central location using wireless sensor nodes. Sensor data are collected continuously and automatically without the need of a human worker. We believe this type of application will be widely deployed because of (a) the low cost of sensors, and (b) the real time feedback they provide in control systems. It has been shown that demand controlled ventilation can save energy [Haghighat and Donnini 1992; Emmerich 1996]. WSNs substantially reduce the cost by removing the need for long cables for communication between sensors and the control center.

2.7 Comparison and Our Contributions

Table I summarizes the capabilities of several related projects. In this table, we adopt the following definitions:

- "Mobility" is the ability of nodes to move over time;
- "Hierarchy" refers to a tiered arrangement of nodes;
- "Learning" indicates the ability to estimate correct values at run time;
- "Resource Efficient" shows if hardware resource usage is a concern;
- "Aggregation" is the ability to combine data;
- "Designed for Security" states whether security is a main goal of the design;
- "Add/Remove nodes" shows if it is possible to change the number of nodes at run-time.

Table I. Matrix of Capabilities of Fault Observation Methods: Sympathy [Ramanathan et al. 2005], DICAS [Khalil et al. 2005], Daicon [Ernst et al. 2001], DIDUCE [Hangal and Lam 2002]

	H-SEND	Sympathy	DICAS	Send to Base	Daicon	DIDUCE
Mobility	Yes	Yes	Yes	Yes	No	No
Hierarchy	Yes	No	Yes	Yes	No	No
Learning	Yes	Not Yet	No	No	Yes	Yes
Resource Efficient	Yes	Yes	Yes	No	No	No
Aggregation	Yes	Yes	No	Yes	No	No
Designed for Security	No	No	Yes	No	No	No
Add/Remove Nodes	Yes	No	Yes	Yes	No	No

Sympathy [Ramanathan et al. 2005] transmits metrics such as network link quality and routing stability back to the base station for analysis. Sympathy assumes high throughput of the network and all data for correctness checking are sent to the base station. Dicas [Khalil et al. 2005] places additional nodes to monitor wireless communication for detecting faults. Send-to-base is a simple method where the developer manually inserts code to send all variables to be monitored back to the base station. Daicon [Ernst et al. 2001] and DIDUCE [Hangal and Lam 2002] observe the behavior of programs to automatically create invariants; developers are not required to specify invariants. Automatic creation is performed by first creating strict invariants. As the programs execute, the invariants are gradually relaxed to accommodate new correct behavior. Neither Daicon nor DIDUCE is designed for distributed or resource-constrained systems like WSNs.

This article extends our previous work [Herbert et al. 2006] where we introduce-observing variables specified by a developer through invariants to detect faults. This prior work used invariants determined at compile-time. In addition, we have investigated capturing data trends over time in [Herbert et al. 2007a], where we used data modeling to reduce the amount of transmission overhead. We explored the benefits CO_2 and temperature monitoring in real world applications in [Herbert et al. 2007b]. This article includes a detailed study of how to use the same infrastructure with the addition of invariants that have run-time determined parameters, and validates this approach on data collected from real sensors. We deploy a WSN to measure indoor $\mathrm{CO_2}$ and temperature levels, and demonstrate that our framework can correctly detect data trends and sudden changes of the levels as violations of invariants.

3. TECHNIQUES FOR FAULT DETECTION, DIAGNOSIS, AND REPAIR

3.1 Overview

Our system determines the health of a WSN by detecting software faults or sudden changes of data trends, propagating the information to the base station, assisting a programmer to diagnose the faults, and then distributing correct software after the programmer fixes the faults. Our approach addresses "What is observed and when?" and "How is a fault detected?"

3.1.1 *What Is Observed and When?*

Invariants are classified in several ways:

Local invariants are formed from variables resident on the same node (henceforth referred to as local variables, not to be confused with local variables within a function) only and *multinode invariants* from a mix of local and nonlocal variables. Local invariants can be checked at any point where the constituent variables are in scope, while remote invariants can be checked when the set of network messages carrying all the nonlocal variables have been successfully received and the local variables are in scope.

Stateless invariants and *stateful invariants*. Stateless invariants are always true for the node, irrespective of the node's operation states. Stateful invariants are true only when the node is in a particular execution state.

Compile-time determined invariants and *Run-time determined invariants*. Compile-time determined invariants compare variables and program conditions against values that do not change. Run-time determined invariants use *spatial trending* to compare variables and program conditions against other neighboring nodes. *Temporal trending* compares against prior history. An example of a compile-time determined invariants is "Sensed temperature is between 10 and 30 degrees Celsius." An example of a run-time determined invariant utilizing history is "Temperature does not change by more than 10% in a period of 60 seconds." A run-time determined invariant can check the condition "All nodes report temperatures that are within 1 standard deviation of each other." H-SEND allows different classes of invariants to detect different faults.

3.1.2 *How Is a Fault Detected?*

A fault is detected when one or multiple invariants are violated. The verification of a local invariant involves some computation without additional communication. One of the benefits of performing temporal trending is that expensive communication is required only when a fault is detected. The verification of a remote invariant involves additional communication. Spatial trending requires communication energy to propagate values, but requires less memory because a history buffer does not need to be kept. WSNs are energy bound so nodes are often put to sleep to conserve energy; sending debug information separately can use a significant amount of energy. An alternative is to piggyback invariant information onto data messages that contain sensed data. This reduces the cost of communication—the fixed cost is amortized. Additionally, this removes interference with any existing node sleep-awake protocol. However, this implies that the fault can be propagated only when a data message is generated. Such delay, fortunately, is bounded and an analysis is presented in Section 4.4.

3.2 Invariant Grammar

Invariants are specified in source code in the form:

```
[scope modifier() [where (condition modifier)]] require (rule);
```

An example is `forall(HS_NODES) where (node==HS_CLUSTERHEAD) require (a < MAX_HOPS)`. `HS_NODES` refers to all nodes, and `HS_CLUSTERHEAD` refers to the current cluster head. This invariant checks that `a` is less than `MAX_HOPS`.

The scope modifier may include `forall` or `exists`. If there is no scope modifier, the invariant only applies to the local node. The scope modifier `forall` indicates that the invariant holds for every node. The scope modifier `exists` indicates that it holds for at least one node. The condition modifier `where` indicates that a condition is present to act as a filter upon the scope. Several enumerated values are available to use for this purpose: `HS_NODES` for all nodes, `HS_CLUSTERHEAD` for cluster heads, and `HS_BASESTATION` for the base station. Local and remote variables can also be used. The `rule` may use remote variables, local variables, variables from a single function, or variables from multiple functions, in defining the expression.

Placement will specify the scope of an invariant. If an invariant is to hold for a single statement, then the specification is placed immediately after that statement. If an invariant is specified for an entire function, then the specification is placed at the beginning of the function body. If an invariant must be satisfied no matter which function is being executed, then the specification is placed at the beginning of a program module: a source file in the NesC language.

The `forall` scope modifier can be applied to functions. The entire set of functions is denoted by `HS_FUNCTIONS`. For example, `forall(HS_FUNCTIONS) require (HS_CLUSTERHEAD == message.sender);` means that the sender of any message must be the current cluster head, regardless of which function is being executed. Receiving a message from any other node indicates a fault. Additionally, we identify the most recently received message by the variable `M_IN`, and the most recently sent message by the variable `M_OUT`. The node identification number is `NODE_ID`. The `forall` and `exists` quantifiers can be applied to both messages and node IDs. The fields `.sender` and `.type` can be accessed for messages. For all data, the `.age` field is incremented each time a new piece of data is sampled and evaluated, and can be used to perform historical analysis. For example, `forall(M_IN) where ((M_IN.type == M5) && (M_IN.age < 20)) require (M_IN.sender == 5);` reads "For the last 20 messages received, all messages of the M5 type must come from node number five."

In the prior example, the value "5" is determined at compile-time and checked at run-time. This restricts the applicability of invariants because some values may be specific to the deployment environment. A programmer does not have to rely on compile-time values when creating invariants. Run-time determined values can be used for invariants by using *spatial trending* or *temporal trending*. The former compares a value against the values from neighboring nodes; the latter compares the current value with earlier values. To specify trending, one can use the additional reserved keyword `trend`; it allows WSN developers to specify invariants using run-time determined values. One example of trending is to detect the mean μ and the standard deviation σ of sensed data.

An example of a trending invariant is `forall (sensedData) where (sensedData.age < 10) require (trend(sensedData,1))`, which allows a program to perform temporal trending and compare sensed data over time, and trigger a fault message. If any sensed value is more than one standard deviation away from the mean of the last 10 samples, a fault is detected. Another invariant, `forall (HS_NODES) require (trend(sensedData,1))`, performs spatial trending by comparing an individual node's data against the values

Table II. Messages Used for Cluster Formation

Message	Function
M1: Election	Initiate the election process for a CH (cluster head)
M2: Data	Send sensed data from a node to a CH
M3: Aggregate Data	Aggregate data in a CH and send to base station
M4: I'm a new CH	Inform the nodes that the sender is a new CH
M5: I'm a CH	Send periodic "keep-alive" to nodes in the cluster
M6: My CH is unavailable	Realize my CH is unreachable and send to the base station
M7: Relieve CH	Inform the other nodes that the CH intends to relinquish its role due to, for example, impending energy exhaustion

collected by all the other nodes. A violation occurs if the difference exceeds one standard deviation.

3.3 Invariant Examples

H-SEND can be used to detect data trends and faults in WSN operations, such as leader election, time synchronization, and location estimation. We use leader election as an example here and in Section 4 to illustrate H-SEND's capability. We use several types of messages as examples, listed in Table II. Message "M1: Election" initiates an election, upon which nodes randomly respond by sending "M4: I'm a new cluster head" to other nodes, and the old cluster head responds with "M7: Relieve cluster head." Sensing nodes then send "M2: Data" messages to the cluster head, which combines the messages and sends "M3: Aggregate Data" to the base station. If a cluster head disappears, a node will broadcast "M6: My cluster head is unavailable" to all nodes.

The invariants listed below can be specified in the program, using the format shown in Section 3.2. The following list shows (a) possible invariants for the protocol in English, (b) the invariant specification grammar, (c) whether the invariant has fixed parameters (compile-time) or the system learns parameters (run-time), (d) the invariant is stateful, and (e) what type of fault is detected.

1. Rule: If a node detects unavailability of a cluster head, a new cluster head should take over within `X` time units:
   Invariant: `forall(M_OUT) exists(M_IN) where ((M_OUT.type == M6) && (M_IN.type == M4)) require ((M_IN.time - M_OUT.time > 0) && (M_IN.time - M_OUT.time < X));`
   NesC checking code inserted by H-SEND code augmenter:

```
int lastM4MinMsgTime;

if((M_OUT == M6) && (((lastM4MinMsgTime - M_OUT.time) < 0) ||
  ((lastM4MinMsgTime - M_OUT.time) > X))) {
  /* Create and send fault packet*/
}

if(M_IN.type == M4)
  lastM4MinMsgTime = M_IN.time;
```

   Type: Compile-time/Stateful/Implementation Fault

2. Rule: A node is no more than `X` hops from a cluster head:
   Invariant: `forall(HS_NODES) where (M_IN.sender == HS_CLUSTERHEAD) require (M_IN.hops <= X);`
   NesC checking code inserted by H-SEND code augmenter:

```
if((M_IN.sender == HS_CLUSTERHEAD} && (M_IN.hops > X) {
  /* Create and send fault packet*/
}
```

   Type: Compile-time/Stateless/Scalability Fault

3. Rule: Sensed data value stored in variable sensedValue does not differ among nodes by more than 3 standard deviations.
   Invariant: `forall(HS_NODES) require (trend(sensedValue,3));`
   NesC checking code inserted by H-SEND code augmenter to be evaluated at base station:

```
//Retain values between calls
static int data[MAX_NODES]; static int index = 0;
int i; int mean = 0; int stddev = 0;

// Insert into array with latest data from other nodes.
data[NODE_ID] = M_IN.sensedValue;

// Calculate Mean
for(i = 0; i < MAX_NODES; i++) { mean += data[i]; }
mean = mean / MAX_NODES;

// Calculate Standard Deviation
for(i = 0; i < MAX_NODES; i++) { stddev += (data[i] -
mean)^2; }
stddev = sqrt(stddev/MAX_NODES);

// Check against tolerance
for(i = 0; i < MAX_NODES; i++)
  if((data[i] < (mean - 3*stddev)) || data[i] >
  (mean + 3*stddev)))
    { /* Create and send fault packet*/ }
```

   Type: Run-time/Stateful/Scalability Fault

From the list of examples, we can see that checking invariants in not an onerous task. The computation is small, consisting of an equality or inequality check, and calculating the conjunction or disjunction of multiple Boolean values.

4. CASE-STUDY: DEBUGGING A DISTRIBUTED LEADER ELECTION PROTOCOL

In this section we demonstrate the capabilities the H-SEND fault detection approach. We implement leader election to show a wide range of compile-time determined invariants. We use data collected from our testbed of CO_2 and temperature sensors to show how to determine the history size and tolerance needed to effectively use run-time determined invariants.

4.1 LEACH

We implemented the LEACH (Low-Energy Adaptive Clustering Hierarchy) cluster based leader election protocol for WSNs [Heinzelman et al. 2002, 2000]. In LEACH, the nodes organize themselves into clusters, with one node acting as the head in each cluster. LEACH randomizes which node is selected as the head in order to evenly distribute the responsibility among nodes and to prevent draining the battery of one node too quickly. A cluster head compresses data (also called *data fusion*) before sending the data to the base station. LEACH assumes that all nodes are synchronized and divides election into rounds. Nodes can be added or removed at the beginning of each round. In each round, a node decides whether to become a head using the following probability. Suppose p is the desired percentage of cluster heads (5% is suggested in Heinzelman et al. [2002]). If a node has not been a head in the last $\frac{1}{p}$ rounds, the node chooses to become a head with probability $\frac{p}{1-p\times(r \bmod \frac{1}{p})}$, where r is the current round. After $\frac{1}{p}$ rounds, all nodes are eligible to become cluster heads again. If a node decides to become a head, the node broadcasts a message to the other nodes. The other nodes join a cluster whose leader's broadcast message has the greatest signal strength. In the case of a tie, a random cluster is chosen. LEACH is used in many other studies, such as Lindsey et al. [2002], Min et al. [2001], and Muruganathan et al. [2005]; because LEACH is efficient, simple to implement, and resilient to node faults.

Figure 4 shows the states of the LEACH protocol. Each solid arrow indicates an event that causes a state change, and each dashed arrow indicates a communication message. Invariants can easily be created from this state diagram. If a node is in a certain state, and any event occurs for which the state diagram is not defined, a fault has occurred. Possible invariants for the LEACH protocol include "only in the 'Wait for Join Message State' should a 'Join Message' be received" or "A node should only receive a 'TDMA schedule' in the 'wait for TDMA schedule state.' " The compiler can then insert code for these compile-time invariants to check the health of a node or the network.

4.2 Carbon Dioxide and Temperature Measurement

A picture of a sensor node from our data collection test bed is shown in Figure 5. Each sensor node contains a Crossbow MPR400CB (Mica2) sensor mote coupled to a SenseAir aSense carbon dioxide (CO_2) and temperature sensor through a custom interface circuit. Power is supplied to the CO_2 and temperature sensor by an unregulated 24 volt AC transformer. A 5 volt transformer is regulated

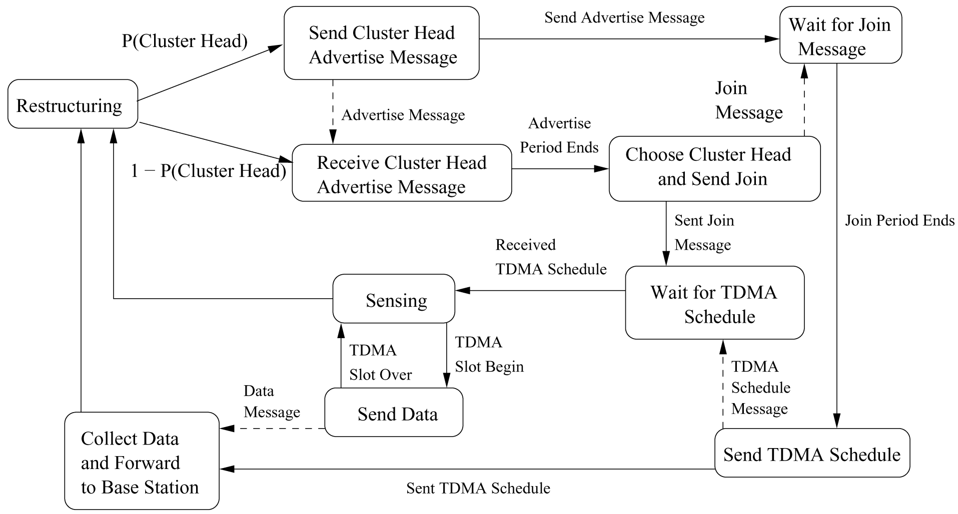


Fig. 4. State diagram of the LEACH protocol.

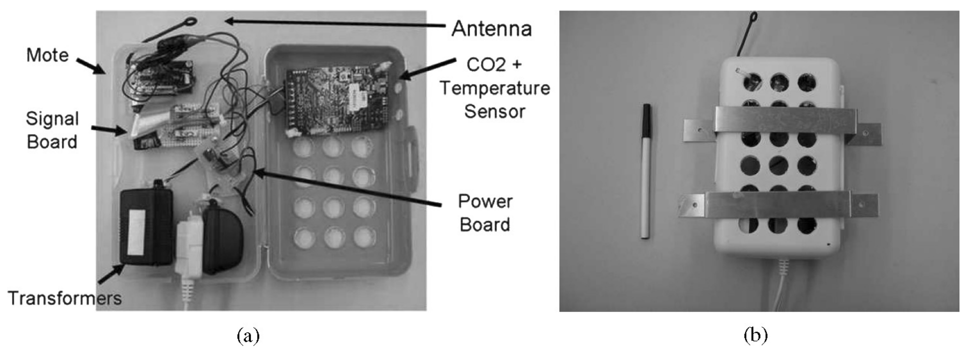


Fig. 5. CO_2 and Temperature Sensing Node, (a) The internal components, (b) The node as seen from the outside (ink pen is shown for size reference).

to 3 volts by an external voltage regulation circuit and provides power to the rest of the interface board and the sensor mote. The interface board scales the analog output of the aSense to a range acceptable to the mote, and adds diode limiters to protect the sensor mote from electrical damage. All circuits use precision potentiometers that were tuned using a digital multimeter to reduce losses in accuracy due to power fluctuations and signal scaling. The CO_2 and temperature data are sensed by the onboard 10-bit analog to digital converter of the mote, and forwarded to the base station where the values are recorded and archived.

4.3 Examples of Invariant Violation

At present, all invariants are manually inserted but insertion can be done by a compiler as explained in Section 3.3. This automatic invariant-insertion tool is under development. In our experiments, we originally intended to write "correct" code first and then intentionally inject faults later. However, we encountered unexpected behavior by the nodes and decided to insert invariants first to help us isolate the fault (or faults). We observed that some nodes entered the "Cluster Head Advertise" state at the wrong time. The fault was a state-transition violation. An invariant required that "Restructuring State" be the previous state before the "Send Cluster Head Advertise Message" state. This is a binary example: there is only one correct previous state. If the previous state is incorrect, the invariant is violated. After this invariant was inserted, we discovered a fault in our LEACH implementation. When the invariant was violated, a fault was reported at the node level. Without this distributed debugging system, a simple fault would have been difficult to diagnose. This shows that a binary invariant can be very helpful. An invariant can also include numeric quantities. For example, we can observe the signal strength received by each node in order to analyze the health of the network. An invariant can be written to ensure that the signal strength from a cluster head does not vary above 50%. If this invariant is violated, a fault is reported. This report can assist the protocol designer to decide whether a more robust (and higher overhead) protocol should be chosen.

4.4 Analysis

This section analyzes the overhead, time to detect faults, trending parameter selection, and code size.

4.4.1 *Network Traffic Scaling.* Since sensor nodes have limited energy, they should send as little information as possible to conserve energy. LEACH uses data fusion to reduce the amount of network traffic. We analyze the network overhead of H-SEND as follows. Let m_c and m_b represent the size of a message sent from a node to its cluster head and the base station. Let f be the fusion factor. For example, f is 10 if the cluster head summarizes 10 samples and sends the average to the base station. Let δ be the additional amount of information sent by each node for fault detection. The value of δ is zero if no information is transmitted for detecting faults. The total amount of data sent in the whole wireless network can be expressed as $\sum_{\forall x \in \text{nodes}} \sum_{\substack{\text{messages} \\ \text{from } x}} (m_c + \frac{m_b}{f} + \delta)$. One goal of the H-SEND approach is to minimize the communication overhead. Suppose m_1 is the total amount of information transmitted in the network without any detection messages ($\delta = 0$). Let m_2 be the amount of information with detection messages. The overhead is defined as $\frac{m_2 - m_1}{m_1}$. In H-SEND, nodes only forward debugging data to cluster heads, and cluster heads only forward debugging data to the base station (i.e. upwards). No debugging data are sent back down to nodes from higher levels of the hierarchy. The rationale is that diagnosis only needs to aggregate information. Therefore, adding nodes results in a linear increase in network traffic. The case study presented here observed three variables at the cluster level, and six variables at the network level. Figure 6 shows that the traffic grows linearly for network sizes between 5 and 125 nodes. This figure shows three lines: (a) no fault detection. (This has the same amount of traffic as node-level detection.) (b) cluster-level detection, and

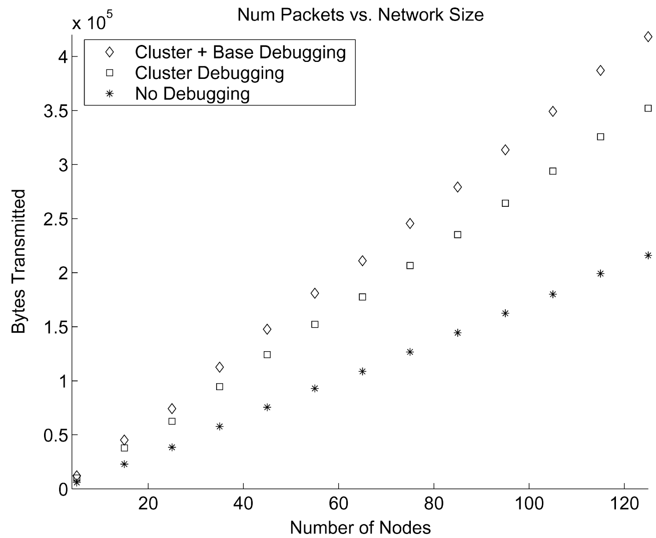
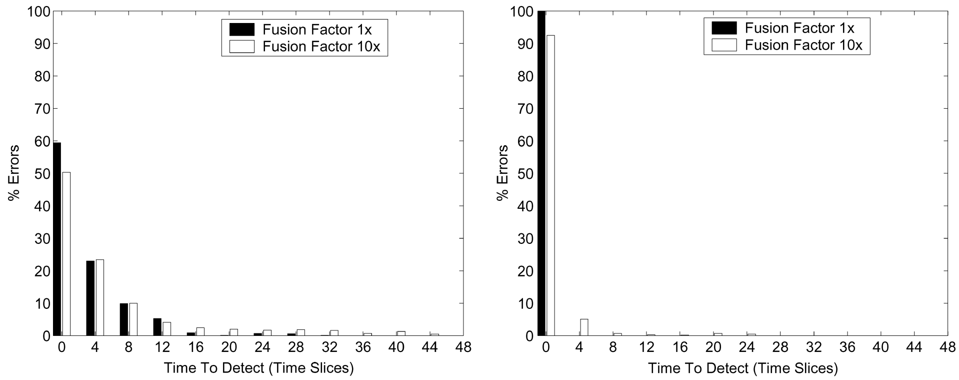


Fig. 6. Network traffic vs. network size.

(c) cluster and base-level detection. The vertical axis shows the number of bytes transmitted. The actual amount depends on the duration of the simulated network. Regardless of the duration, the ratio of $\frac{(b)}{(a)}$ and $\frac{(c)}{(a)}$ is approximately 1.64 and 1.95, respectively. In other words, the percentage of the network overhead is nearly a constant. Detecting faults as close to the source as possible allows H-SEND to reduce the amount of traffic sent over the network. The worst case scenario is to send all data to the base-station, and perform data-analysis at the base station. Through simulation, it was found that the H-SEND method resulted in a 7% message reduction size vs. sending all data needed to evaluate invariants to the base station.

4.4.2 *Detection Time.* To further reduce network traffic, observed detection data are piggybacked onto data messages through the network as part of normal operation. This saves the fixed cost of communicating a new packet, such as the cost of the header bytes accompanying each packet (7 bytes out of the default size of 36 bytes for the Mica2 platform). Piggybacking data adds a bounded latency to detection, as data are held at the node or cluster level until a data message is sent to the next level. Due to bounded detection time, all faults are reported, and there are no losses. If piggybacking is not used, fault propagation delay is of the order of communication delay. If the fault is delay sensitive, an additional strategy that can be used in addition to piggybacking is generating an explicit control message if the delay goes above a threshold. Detection time is defined as the time period between when a node detects a fault, and the base station receives the message indicating a fault. The worst-case detection time occurs when a node transmits data in the first transmit slot and detects a fault in the very next slot, and must wait for all nodes in it's cluster to transmit (n-1 slots). It must then wait for the network to restructure, and then the same node must be assigned to the last transmit slot (n-1 slots). Analytically,



(a) (b)

Fig. 7. Simulated results for detection time, (a) Node-level, (b) Cluster-level.

we can define the worst case detection time as: $2 \times$ (Number of Transmit Slots-1) $+$ Number of Slots to Restructure. This equation was confirmed by simulation. The LEACH protocol has 4 slots of administrative overhead. In Heinzelman et al. [2000] it is found that 5% of nodes acting as cluster heads is ideal, yielding an average cluster size of 20 nodes with 20 time slots to broadcast results. Using these parameters, the worst-case detection time is 42 time slots. The data fusion factor will affect the detection time, as higher fusion factors result in fewer messages. As a result, detection time increases when the fusion factor increases. Figure 7(a) shows a histogram of node-level detection time at fusion factors of 1 and 10. As the figure shows, most faults can be detected within 4 time slots. When the fusion factor is higher, the figure shows that detection time increases. Figure 7(b) shows the detection time for cluster level fault detection. The detection time is significantly less than at the node level, because cluster heads communicate with the base station much more often.

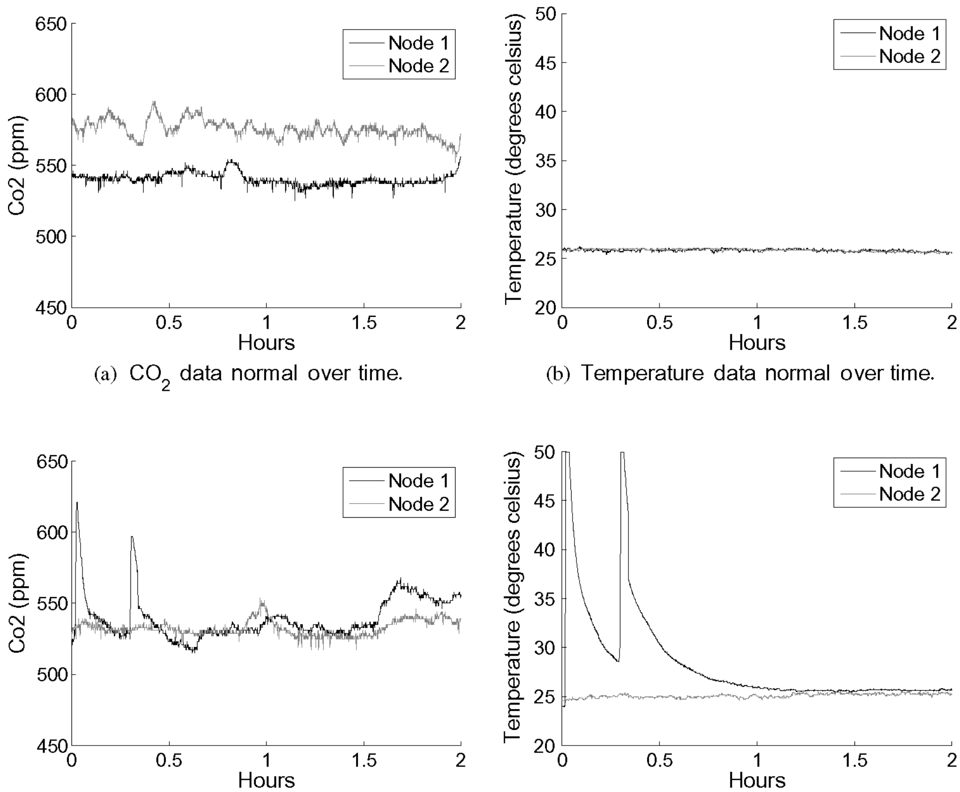
4.4.3 *Choosing Trending Parameters.* Trending accuracy is closely related to the tolerance allowed. In our experiments, the tolerance is measured by multiples of the standard deviation $x \cdot \sigma$. The natural amount of variation in a WSN is sensor and environment specific. Harsh environments may correctly sense a large amount of variation with no fault occurrences, such as seismic sensors for earthquakes. Many applications, however, will report a small amount of variation, such as indoor CO_2 sensing. To determine the tolerance (x), one must consider what variation is seen in normal operating conditions, and choose a tolerance slightly above this. If x is too small, normal runtime variance will trigger faults. If x is too large, faults may not be detected. Hence, x must be larger than the natural variation of correct data, but smaller than abnormal sudden changes. The WSN developer must also determine the amount of history to use (y samples) for temporal trending. If y is too small, the amount of history is insufficient to observe the trend. If y is too large, the trend is influenced by data collected in the remote past. The history size (y above) is also directly related to the amount of memory temporal trending consumed at run-time, and therefore it is desirable to chose the smallest history size that can capture enough data to locate faults. We show in the following paragraphs how to determine appropriate values for both x (the tolerance) and y (the history size) for trending based on empirical data.

To demonstrate a real world example of choosing the proper tolerance and history size, we collected data from two CO_2 and temperature sensors placed on different sides of an approximately 50 square meter lab with two occupants for 2 hours under normal air conditions. Care was taken not to perturb the environment. Normal building ventilation was present, and the single door to the hallway was left open to simulate normal conditions. Data were sampled every 30 seconds, and the base station logged the data to permanent storage during collection. We repeated the data collection with a student temporarily holding a 1500 Watt personal hair dryer to one node at two different times during the experiment. The hair dryer causes a quick spike in temperature to 50 degrees Celsius, the maximum temperature the sensor can measure. Additionally, we recorded an increase in CO_2 level when the student was operating the hair dryer, from the increase in air flow over the sensor and the close proximity of the student. We use this data collected with the hair dryer to represent a malfunctioning sensor or a sudden change of the environment. The CO_2 and temperature data of both the normal case, and the hair dryer case are shown in Figure 8.

To evaluate trending performance across a wide range of tolerances and history sizes, we inserted this data into a TOSSIM simulation, where nodes use the data as their sensed values in a 20 node simulation of a network running the LEACH protocol. TOSSIM allows us to use the same sensed data in multiple simulations of different tolerance and history values. The sensed data from node 1 simulated the sensed data for one node, the data from node 2 simulated sensed data for 18 other nodes, and the remaining node served as the base station. We inserted run-time determined invariants into the application code to perform trending on (1) the time between cluster elections, (2) the number of members in an individual cluster, (3) the number of clusters, (4) the number of bytes transmitted between elections, (5) the value of the sensed CO_2 data, and (6) the value of the sensed temperature data.

To determine the appropriate tolerance for spatial trending, we simulated a network performing spatial trending with tolerances of 1, 2, 3, 4, and 5 standard deviations for the value of x with both the normal data, and the hair dryer data representing faults. We record the number of faults that were detected by trend monitoring, and show the results in Figure 9. At a tolerance of 4 standard deviations no errors are reported for correct data, and 310 errors are reported for the hair dryer simulated fault data. We can see from the figure that a tolerance value lower than 4 shows a similar number of errors in both the correct data and hair dryer data. Tolerances larger than 4 standard deviations do not detect the errors in faulty data, and are therefore too loose.

To determine the appropriate tolerance and history size for temporal trending, we simulated a network performing temporal trending with tolerances from 1 to 5 standard deviations for x, and with history sizes of 4, 8, 16, and 32

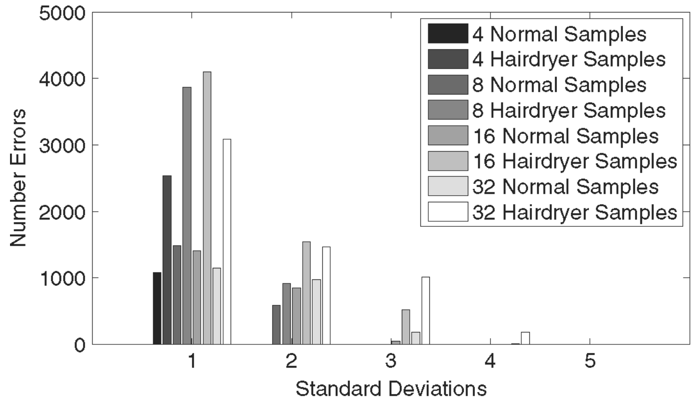


(a) CO_2 data normal over time.
(b) Temperature data normal over time.
(c) CO_2 data with hairdryer over time.
(d) Temperature data with hairdryer over time.

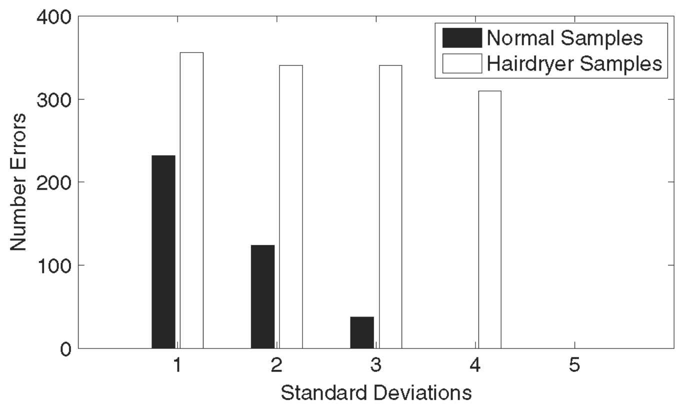
Fig. 8. (a) CO_2 Data and (b) Temperature Data Collected with Normal Conditions (c) CO_2 Data and (d) Temperature Data Collected with Hair Dryer induced Fault Conditions.

sensor readings for y. We simulated nodes sensing both correct and hair dryer induced faulty data. We counted the errors for each set of parameters and show the results in Figure 9. A history size of 16 sensed readings, with a tolerance of 3 standard deviations shows an order of magnitude more faults in the hairdryer case, compared with the normal data case. A window size of 32 with 4 standard deviations also shows an order of magnitude more faults in the hairdryer case than in the normal data case. In this particular application we find both pairs of parameters to perform excellent temporal and spatial trending. We choose 3 standard deviations ($x = 3$) with a history size of 16 ($y = 16$) due to the reduced memory requirement.

4.4.4 *Code Size.* When implementing the LEACH protocol, all nodes except the base station must use the same binary image because all nodes can be cluster heads at some point. The data reported in Table III was collected with O1 optimization, based on binary images for the Mica2 platform. The column for ROM indicates the code size written to the flash memory. The column for RAM indicates the memory requirement at run-time. The baseline includes the



(a) Temporal trending errors reported from differant history buffer lengths.



(b) Spatial trending errors reported.

Fig. 9. Number of faults for different sigma on normal and erroneous data, (a) Temporal Trending, (b) Spatial Trending.

Table III. Code Size of H-SEND in Bytes

Components	ROM Size	RAM Size
LEACH without observation	11744	1466
LEACH with node level observation	12838	1470
LEACH with node, and cluster level observation	12906	1530
LEACH with node, cluster, and base station level observation	13040	1639

program that performs the basic sensor functionality and LEACH leader election. Adding node level observation increases the code size by 9% ($\frac{12838}{11744} - 1$). Adding all levels of observation increases the code size by 11% ($\frac{13040}{11744} - 1$). The increased RAM size comes from the additional bytes in the buffers for each packet.

5. CONCLUSION AND FUTURE WORK

This article presents a hierarchical approach for detecting software faults for WSNs. The detection is divided into multiple levels: node, cluster, and base station. Programmers specify the conditions (called invariants) that have to be satisfied. Correct values can be specified in source code and determined at compile-time, or trending can be used to determine correct value ranges at run-time. It is possible to automatically insert invariants by a compiler. Our method is distributed and has low overhead in code size and network traffic. Our method can be applied to a wide range of protocols. We use a leader election protocol as a case study, and show run-time trending on CO_2 and temperature data. The H-SEND approach is designed to be tied into other existing technologies. For future work, we will address ways of detecting scenarios that trend monitoring cannot detect, such as sensor calibration shifting. We plan to implement automatic invariant insertion by a compiler.

REFERENCES

An Huang, Y. and Lee, W. 2003. A cooperative intrusion detection system for ad hoc networks. In *ACM Workshop on Security of Ad Hoc and Sensor Networks*. 135–147.

Buchegger, S. and Boudec, J.-Y. L. 2002. Performance analysis of the CONFIDANT protocol. In *ACM International Symposium on Mobile Ad Hoc Networking & Computing*. 226–236.

Diaz, M., Juanole, G., and Courtiat, J.-P. 1994. Observer—A concept for formal on-line validation of distributed systems. *IEEE Trans. Softw. Engin.* 20, 12.

Dolev, S., Israeli, A., and Moran, S. 1997. Uniform dynamic self-stabilizing leader election. *IEEE Trans. Para. Distrib. Syst. 8*, 4 (Apr.), 424–440.

Emmerich, S. 1996. Demand-controlled ventilation in a multi-zone office building. *Fuel and Energy Abstracts 37*, 4, 294–294.

Erdmann, C. A., Stiener, K. C., and Apte, M. G. 2002. Indoor carbon dioxide concentrations and sick building syndrome symptoms in the base study revisited: Analysis of the 100 building dataset. In *Indoor Air*. 443–448.

Ernst, M. D., Cockrell, J., Griswold, W. G., and Notkin, D. 2001. Dynamically discovering likely program invariants to support program evolution. *IEEE Trans. Softw. Engin. 27*, 2 (Feb.), 99–123.

Goldsmith, S., O'Callahan, R., and Aiken, A. 2005. Relational queries over program traces. In *ACM SIGPLAN Conference on Object Oriented Programming Systems Languages and Applications*. 385–402.

Haghighat, F. and Donnini, G. 1992. IAQ and energy-management by demand controlled ventilation. *Environ. Techno. 13*, 4, 351–359.

Hamlet, D. 2005. Invariants and state in testing and formal methods. In *ACM SIGPLAN-SIGSOFT Workshop on Program Analysis for Software Tools and Engineering*. 48–51.

Hangal, S. and Lam, M. S. 2002. Tracking down software bugs using automatic anomaly detection. In *International Conference on Software Engineering*. 291–301.

Heinzelman, W. B., Chandrakasan, A. P., and Balakrishnan, H. 2002. An application-specific protocol architecture for wireless microsensor networks. *IEEE Trans. Wireless Comm. 1*, 4 (Oct.), 660–670.

Heinzelman, W. R., Chandrakasan, A., and Balakrishnan, H. 2000. Energy-efficient communication protocol for wireless microsensor networks. In *Hawaii International Conference on System Sciences. 2*, 1–10.

Herbert, D., Lu, Y.-H., Bagchi, S., and Li, Z. 2006. Detection and repair of software errors in hierarchical sensor networks. In *IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing*. 403–410.

Herbert, D., Modelo-Howard, G., Perez-Toro, C., and Bagchi, S. 2007. Fault tolerant ARIMA-based aggregation of data in sensor networks. *IEEE International Conference on Dependable Systems and Networks*.

HERBERT, D., SUNDARAM, V., ALBIN, L., LU, Y.-H., BAGCHI, S., AND LI, Z. 2007. Pervasive carbon dioxide and temperature monitoring utilizing large numbers of low-cost wireless sensors. *American Industrial Hygiene Conference and Expo*. 163.

HILL, J. L. AND CULLER, D. E. 2002. Mica: A wireless platform for deeply embedded networks. *IEEE Micro. 22*, 6 (Nov.-Dec.), 12–24.

HUI, J. W. AND CULLER, D. 2004. The dynamic behavior of a data dissemination protocol for network programming at scale. In *International Conference on Embedded Networked Sensor Systems*. 81–94.

KHALIL, I., BAGCHI, S., AND NINA-ROTARU, C. 2005. DICAS: Detection, diagnosis, and isolation of control attacks in sensor networks. In *International Conference on Security and Privacy for Emerging Areas in Communications Networks*. 89–100.

KHALIL, I., BAGCHI, S., AND SHROFF, N. B. 2005. LITEWORP: A Lightweight Countermeasure for the Wormhole Attack in Multihop Wireless Networks. In *IEEE International Conference on Dependable Systems and Networks*. 612–621.

KHALIL, I., BAGCHI, S., AND SHROFF, N. B. 2006. MOBIWORP: Mitigation of the wormhole attack in mobile multihop wireless networks. In *IEEE International Conference on Security and Privacy in Communication Networks*.

KHANNA, G., VARADHARAJAN, P., AND BAGCHI, S. 2004. Self checking network protocols: A monitor based approach. In *International Symposium on Reliable Distributed Systems*. 18–30.

KUMAR, N., CHILDERS, B. R., AND SOFFA, M. L. 2005. Low overhead program monitoring and profiling. In *ACM SIGPLAN-SIGSOFT Workshop on Program Analysis for Software Tools and Engineering*. 28–34.

LAMPORT, L., SHOSTAK, R., AND PEASE, M. 1982. The byzantine generals problem. *ACM Trans. Program. Lang. Syst. 4*, 3 (July), 382–401.

Levis, P., Lee, N., Welsh, M., and Culler, D. 2003. TOSSIM: Accurate and scalable simulation of entire tinyOS applications. In *International Conference on Embedded Networked Sensor Systems*. 126–137.

LIAO, C.-M., CHANG, C.-F., AND LIANG, H.-M. 2005. A probabilistic transmission dynamic model to access indoor airborne infection risks. *Risk Analysis. 25*, 5, 1097–1107.

LINDSEY, S., RAGHAVENDRA, C., AND SIVALINGAM, K. M. 2002. Data gathering algorithms in sensor networks using energy metrics. *IEEE Trans. Paral. and Distrib. Syst. 13*, 9 (Sept.), 924–935.

LYNCH, N. A. 1996. *Distributed Algorithms*. Morgan Kaufmann.

MAHANEY, S. R. AND SCHNEIDER, F. B. 1985. Inexact agreement: Accuracy, precision, and graceful degradation. *ACM Symposium on Principles of Distributed Computing*. 237–249.

MARTI, S., GIULI, T. J., LAI, K., AND BAKER, M. 2000. Mitigating routing misbehavior in mobile ad hoc networks. In *International Conference on Mobile Computing and Networking*. 255–265.

MARZULLO, K. 1990. Tolerating failures of continuous-valued sensors. *ACM Trans. Comput. Syst., 8*, 4 (Nov.), 284–304.

MEDIDI, S. R., MEDIDI, M., AND GAVINI, S. 2003. Detecting packet-dropping faults in mobile ad-hoc networks. In *IEEE ASILOMAR Conference on Signals, Systems and Computers*.

MILTON, D. K., GLENCROSS, P. M., AND WALTERS, M. D. 2000. Risk of sick leave associated with outdoor air supply rate, humidification, and occupant complaints. *Indoor Air 10*, 4 (Dec.), 212–221.

MIN, R., BHARDWAJ, M., CHO, S.-H., SHIH, E., SINHA, A., WANG, A., AND CHANDRAKASAN, A. 2001. Low-power wireless sensor networks. In *International Conference on VLSI Design*. 205–210.

MURUGANATHAN, S. D., MA, D. C. F., BHASIN, R. I., AND FAPOJUWO, A. O. 2005. A centralized energy-efficient routing protocol for wireless sensor networks. *IEEE Commun. Mag. 43*, 3 (Mar.), 8–13.

MYATT, T. A., JOHNSTON, S. L., ZUO, Z., WAND, M., KEBADZE, T., RUDNICK, S., AND MILTON, D. K. 2004. Detection of airborne rhinovirus and its relation to outdoor air supply in office environments. *Amer. J. Respir. Critic. Care Med. 169*, 1187–1190.

NAKANO, K. AND OLARIU, S. 2002. A survey on leader election protocols for radio networks. In *International Symposium on Parallel Architectures, Algorithms and Networks*. 63–68.

NASIPURI, A., CASTANEDA, R., AND DAS, S. R., 2001. Performance of multipath routing for on-demand protocols in mobile ad hoc networks. *Mobile Netw. Appl. 6*, 4, 339–349.

PERKINS, J. H. AND ERNST, M. D. 2004. Efficient incremental algorithms for dynamic detection of likely invariants. In *ACM SIGSOFT International Symposium on Foundation of Software Engineering*. 23–32.

PIRZADA, A. A. AND MCDONALD, C. Establishing trust in pure ad hoc networks. In *Conference on Australasian Computer Science*.

RAMANATHAN, N., CHANG, K., KAPUR, R., GIROD, L., KOHLER, E., AND ESTRIN, D. 2005. Sympathy for the sensor network debugger. In *International Conference On Embedded Networked Sensor Systems*. 255–267.

RUDNICK, S. N. AND MILTON, D. K. 2003. Risk of indoor airborne infection transmission estimated from carbon dioxide concentration. *Indoor Air 13*, 3 (Sept.), 237–245.

SEPPANEN, O. A., FISK, W. J., AND MENDELL, M. J. 1999. Association of ventilation rates and CO2 concentrations with health and other responses in commercial and institutional buildings. *Indoor Air*. 226–252.

SINGH, G. 1996. Leader election in the presence of link failures. *IEEE Trans. Paral. Distrib. Syst. 7*, 3 (March), 231–236.

SMITH, B. R., MURTHY, S., AND GARCIA-LUNA-ACEVES, J. J. 1997. Securing distance-vector routing protocols. In *Proceedings of the Symposium on Network and Distributed System Security*. 85–92.

SORO, S. AND HEINZELMAN, W. B. 2005. Prolonging the lifetime of wireless sensor networks via unequal clustering. In *IEEE International Parallel and Distributed Processing Symposium*, page 236b.

TEL, G. 1991. *Topics in Distributed Algorithms*. Cambridge University Press, Chapter 3: Assertional Verification.

VIGNA, G., GWALANI, S., SRINIVASAN, K., BELDING-ROYER, E. M., AND KEMMERER, R. A. 2004. An intrusion detection tool for AODV-based ad hoc wireless networks. In *IEEE Annual Computer Security Applications Conference*.

WANG, J. YI., SHUE, Y.-S., VIJAYKUMAR, T. N., AND BAGCHI, S. 2006. Pesticide: Using SMT processors to improve performance of pointer bug detection. In *IEEE International Conference on Computer Design*.

YEN, I.-L., BASTANI, F. B., AND TAYLOR, D. J. 2001. Design of multi-invariant data structures for robust shared accesses in multiprocessor systems. *IEEE Trans. Softw. Engin. 27*, 3, 193–207.

YOUNIS, M., YOUSSEF, M., AND ARISHA. K. Energy-aware routing in cluster-based sensor networks. In *IEEE International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunications Systems*. 129–136.

YU, I. T., LI, Y., WONG, T. W., TAM, W., CHAN, A. T., LEE, J. H., LEUNG, D. Y., AND HO, T. 2004. Evidence of airborne transmission of the severe acute respiratory syndrome virus. *New Engl. J. Med. 350*, 17 (Apr.), 1731–1739.

ZHOU, Y., ZHOU, P., QIN, F., LIU, W., AND TORRELLAS, J. 2005. Efficient and flexible architectural support for dynamic monitoring. *ACM Trans. Arch. Code Optim. 2*, 1 (March), 3–33.

ZULKERNINE M. AND SEVIORA, R. E. 2002. A Compositional approach to monitoring distributed systems. In *International Conference on Dependable Systems and Networks*. 763–772.

Received March 2006; revised November 2006; accepted May 2007