ABSTRACT
A novel evidence-based approach to energy management in distributed sensor networks (DSNs) is presented. Current approaches and algorithms to DSN energy management are “bottom up” in that they do not consider aspects of the domain of application and particular geographic and environmental situational dynamics to manage energy usage as efficiently as possible. Results from an evidential approach to DSN energy management in a forest fire monitoring and management application are presented. A body of mathematics called evidential reasoning is used to represent and integrate information about the situational dynamics and forest fire detection and monitoring application to draw inferences about the state of nodes in a distributed network. An 18% improvement in energy efficiency compared to the LEACH-C algorithm was observed when the state of the forest environment and knowledge about the dynamics of forest fires are considered managing the state and activity of the DSN. Simulation results using NS2 suggest that the useful life of DSNs can be extended significantly if the situational dynamics and aspects of the domain of application are taken into account.

KEY WORDS
Distributed Sensor Networks, DSN, Evidential Reasoning, Power Management

1. Introduction
Distributed sensor networks (DSNs) are a group of sensor nodes which consists of modules for sensing, processing, communicating data and can be connected through wireless links, as illustrated in Figure 1. Sensor nodes are typically geographically distributed. They route data towards a sink and have limited energy. The main purpose of DSNs is to sense the environment, possibly process sensor data, and forward the information for subsequent interpretation and use by end-users. DSNs are applied in numerous task domains that range from environmental health monitoring, product quality monitoring, intrusion detection, military security, and so forth.

Structured behavior among the nodes can provide advanced capabilities to a distributed sensor network. Organized formation helps to enable and improve basic sensing, such as alerting neighboring nodes whenever there is a change in the surrounding environment, and also managing resources in order to maximize the sensor system’s lifetime. Such data gathering systems usually have an arbitrary and random deployment. The positioning of nodes is usually carried out without taking into account any particular structure or pattern. For instance, sensor node positions might be dependent on the architectural plan of indoor construction, or on geographical features in environmental monitoring scenarios.

Ideally, DSNs are self-configure themselves according to the task for which they are deployed. However, the position of the nodes are typically assumed to be stationary. Node breakdowns and wireless channel dynamics can result in variable network communication topologies. These as well as other DSN dynamics can present significant challenges when trying to maximize energy efficiently and the useful life of a DSN.

To help advance work related to increasing energy efficiencies of DSNs, a novel evidence-based approach is presented where domain knowledge and environmental situational information is integrated to “reason” about the most appropriate energy state of each node. Using an evidential calculus follows from the fact that data and information is, to varying degrees, incomplete, imprecise, and inaccurate. A mathematical calculus called evidential reasoning (ER) has a successful track record of being well suited for representing and reasoning from such types of imperfect information [1-3]. The term evidential comes from the view that at times data and information is better treated as evidence for or against possible conclusions and decisions rather than definitive measurements or probabilistic estimates of the same.
2. Related Work

Several techniques and results of research have been proposed and implemented in this topic area. A rough categorization of such work is illustrated in Figure 2.

Most of the work that is being carried out in power management of distributed sensor networks use data driven approaches or low level domain specific knowledge at one or more of the Physical through Transport Layers [4-7]. Some of this work in this area includes:

- **Power management at Physical layer**

  The core of reliable communication is good modulation scheme which is important for selection. Ultra wideband frequency with pulse position modulation is preferred as it takes low transmission power and has simple transceiver circuitry. Pradhan and Saadavi [5] have proposed energy efficient Distributed Power Management algorithm with Directional Antenna (DDISPOW) that adaptively manages nodes’ power in a dynamic wireless network to preserve network connectivity and reduce interference cooperatively. DDISPOW is a localized asynchronous algorithm that uses directional antenna to adaptively build a stable strongly connected network tailored to its surrounding node density and propagation environment.

- **Power management at Link layer, use of TDMA MAC protocols**

  Work in this area involves cluster-head nomination based on the least amount of energy required to operate in the given condition. Energy efficiency is obtained by grouping the sensors into clusters [8]. Energy efficiency is also be achieved by using schemes such as TDMA (Time Division Multiple Access) scheduling for nodes to periodically sleep then wake up or become idle. Energy is saved when nodes are in either the sleep state or idle state. If a node is down, the routing algorithm recalculates the next hop neighbors.

  At times the path wakeup method is used to save energy instead of a node wakeup scheme, such as used in TDMA [9]. In addition, energy performance comparisons have been made between the S-MAC power consumption method [10] and the adaptive and Always On approach in the link layer [11].

  Additional approaches such as varying the number of nodes in the field, varying the area of interest by deployed nodes, changing delay and arrival rates of traffic have been used to optimize power consumption[12]. To overcome issues with hop by hop routing and increase energy efficiency, Farooq, Dogar and Shah[13] suggested using the MR-LEACH (Multi hop routing with low energy adaptive clustering hierarchy) approach. Clare, Pottie and Agle [14] proposed a Self Organizing approach to achieve power efficiency in DSNs. In this approach, the nodes and network self-organize dynamically depending on a TDMA schedules and necessary communication based on sensed data.

- **Power management at Network layer**

  At the network layer, the main aim is to find ways to achieve energy efficient route setup and reliable relaying of data from the sensor nodes to the cluster head. Lately, the emphasis has been on improving the current routing protocols such as AODV (Ad-hoc on demand distance vector protocol) [15]. RE-AODV is route enhanced ad-hoc on demand routing protocol by M.Usa,S.Jayabharathi and R.S.D WahidaBanu [16] where the resulted protocol has reduction in control overhead and end-to-end delay. Xin Su, DongminChoi, SangmanMoh, Ilyong Chung [17] has proposed a cluster formation algorithm TH-DAECC (Threshold value Density-Aware Energy-Efficient Clustering) where a concept of low and high density clusters is used for routing efficiently. In the steady phase the cluster head of high density cluster will help route the information from low density clusters to send data to the central base station. The cluster head is selected based on the remaining energy in the sensor nodes and distance from the base station.

- **Power management at Application Layer, using cross layering**
3. Forest Fire Domain

According to the Food and Agriculture Organization of the United Nations, around 31% of global land is covered by forest. Around 1% of forest land is consumed by fire each year, resulting in loss of life, negative economic impact, loss of biodiversity, and release of carbon dioxide into the atmosphere [21]. Most forests are monitored using traditional methods that include using watch towers, ground patrols, aerial surveillance, long distance video detection, satellite monitoring, and so forth. Some countries such as Brazil and Canada have started using wireless sensor networks to detect and monitor the progress of forest fires.

Forest fire dynamics will differ depending on a variety of factors. These range from the presence or absence of lightening, regional camping grounds to whether a fire is a crown-fire or not, moisture content, type of the fuel, wind velocity, wind direction, and terrain gradient [21]. We posit that the application of domain knowledge about each of these and other factors can be used to help optimize power utilization in DSNs. For instance, a greater percentage of sensors might be activated in regions experiencing atmospheric lightening activity. Conversely, a greater percentage of sensors might be deactivated during periods of high humidity, rain, or damp fuel conditions. In addition, and everything else being equal, fires tend to travel uphill faster than downhill. If and when a fire is detected in an environment with a terrain gradient, perhaps relatively fewer nodes that are downhill or outside of the fire’s projected path can be active than uphill or in the fire’s expected path. If the objective is to prolong the useful life and energy of DSNs, then the application of domain knowledge in a purposeful manner during pre- and post-fire situations, should in principle, be able to significantly increase energy efficiencies.

To begin to accomplish this, we present two innovations, (1) the use of domain specific knowledge to help assess the situational dynamics and decide which nodes should be active, and (2) the use of the evidential reasoning (ER) calculus to integrate the data and knowledge needed to decide how to help optimize power utilization in a DSN.

The ER calculus can be viewed as a generalization of traditional probabilistic-based calculi. When complete probabilistic and statistical data are available, it has been proven that the ER calculus provides the same quantitative result [2]. However, unlike traditional probabilistic-based methods, if and when complete statistical data are lacking or are unreliable, the ER calculus provides a means to integrate data that to varying degrees is incomplete, imprecise, and inaccurate while providing useful inferential results.

Not all data that is needed to detect, monitor, and reason about forest fires will always be readily available or perfect. At times, data might, at best, only suggest the possible state of an environment or situation rather than a statistical likelihood. Having a mathematically sound and formal means to assess and reason about the situational dynamics of forest fires from imperfect statistical and non-statistical “suggestive” type data is critical to achieving improved energy efficiency in DSNs. For example, to decide which sensor nodes to activate, statistical data about the prevailing wind direction at certain times of the year and day might need to be considered along with the possible locations where lightning might strike. In the absence of sophisticated equipment, it might be that with current sensors the location of lightning strikes can only be suggested based on the direction and intensity of detected thunder. The flexibility of the ER calculus to represent and reason from diverse imperfect data and being a generalization of traditional probabilistic-based calculi is a key motivating factor for its use in this investigation.

Our evidential approach is intended to be applied after nodes have been distributed and organized possibly using existing DSN algorithms. The idea is that additional energy optimization can be achieved over and above existing methodologies by the application of domain knowledge to reason about the situational dynamics and power state of the nodes in a DSN. In our proposed approach, individual sensor nodes are not themselves carrying out any sophisticated and deep reasoning. Rather, a base station, as depicted in Figure 3, has sufficient connected and continuous energy and computational resources to carry out the evidential-based reasoning to infer the optimal power state of each node within a DSN.

3.1 An evidential application to forest fires

In this example, consider a sensor node, in cluster #3 that is shown in Figure 3. The node is on an uphill slope that is located north to north-east of a forest fire that has been detected in lower part cluster #3. For each sensor node, the Base Station receives information from four independent sources of information that include (1) Fire Direction & Velocity (FDV); (2) Wind Velocity & Direction (WVD); (3) Terrain Gradient (TG); and (4)
Relative Node Location (RLN) (i.e., the location of node relative to a fire). When requested by the Base Station, each of these four sources conveys its respective opinion about the state of environment for the specified node based on the sensor’s “observations,” i.e., measurements of the environment. Some of this sensor data might come directly from the node if it is active, some might come from neighboring nodes if active while the node of interest is not, while other data, such as wind velocity, might come from other sensor devices such as an anemometer.

Figure 3 Illustration of ad hoc distributed sensor nodes as might be deployed over a forest by an aircraft.

Suppose the FDV source believes, to a degree of 60%, that a fire is progressing at a slow rate in a North or North East direction. Suppose this same source is also uncertain about the direction and speed of the fire to a degree of 40%. This opinion, can be conveyed, within an ER framework, by the following mass distribution, which consists of one or more proposition-mass pairs such as

\[ m_{FDV}(N - SLOW \lor NE - SLOW) = 0.6, \]
\[ m_{FDV}(\Theta_{FDV}) = 0.4, \]

where \( \Theta_{FDV} \) is a set representing the logical disjunction of all eight directions (N, NE, E, SE, S, SW, W, NW) and three speeds (SLOW, MEDIUM, FAST). In other words, attributing any percentage of belief to \( \Theta_{FDV} \) represents a sensor’s or source’s degree of ignorance (lack of knowledge or data) about the fire direction and velocity.

Further suppose the WVD source is 90% certain that the wind is 0 (i.e., STILL) and uncertain to a degree of 10% about the velocity and direction of the wind. This opinion can be conveyed by

\[ m_{WVD}(STILL) = 0.9, \quad m_{WVD}(\Theta_{WVD}) = 0.1 \]

In addition, suppose the TG (Terrain Gradient) source believes the terrain, relative to our node of interest, is sloped towards a higher elevation in a NE direction (i.e., NE') to a degree of 80%, and uncertain about the terrain gradient to a degree of 20%. This opinion can be conveyed by

\[ m_{TG}(NE +) = 0.8, \quad m_{TG}(\Theta_{TG}) = 0.2 \]

Finally, suppose the RLN (Relative Node Location) source is 80% certain that our node is either near and to the north of the fire, or near and to the north east of the fire, and is uncertain to a degree of 20% about the location of the node relative to the fire. This opinion can be conveyed by

\[ m_{RLN}(N \lor NE \lor NE' \lor N \lor NE) = 0.8, \]
\[ m_{RLN}(\Theta_{RLN}) = 0.2, \]

These opinions, once conveyed, are then propagated through an ER analysis, an example of which, is illustrated in Figure 4, by performing the operation specified at each analysis node.

Figure 4 A graphical representation of an evidential analysis. Nodes in the graph specify operations on data, such as Discounting, Translation, Fusing, and Interpretation to arrive at consensus about the appropriate power state of a node’s antenna.

After the FDV opinion is conveyed, the next node represents the discount operation that adjusts the impact of an opinion based on either its importance relative to other opinions or credibility of the source of the opinion. The credibility of a source or sensor can be characterized in at least two ways. One way is to calibrate the sensor in a controlled laboratory environment. For the FDV sensor, perhaps a grid area where each grid-cell can display a controllable flame of known location and intensity. Experiments can be conducted to record and characterize the accuracy of the FDV sensor as flames in selected grid points are ignited in some temporal manner and direction. The measured accuracy might be input to the ER algorithm in a base station. A second calibration method might involve having the ER algorithms adjust credibility measures of each sensor based on FDV data that are fed back to the base station during or after the fire event.

The credibility value, however it is determined, can then be used to modulate the impact of a sensor’s opinion by reducing the level of support or belief attributed to a
proposition and adding it to the proposition representing total ignorance, \( \Theta_{\text{ECS, Sensor}} \). Using a simplified example, if the credibility of the WVD sensor is 70%, then discounting the

\[
m_{WVD}(\text{STILL}) = 0.9, \quad m_{WVD}(\Theta_{\text{WVD}}) = 0.1
\]
opinion would result in a new discounted opinion of

\[
m_{WVD}(\text{STILL}) = 0.63, \quad m_{WVD}(\Theta_{\text{WVD}}) = 0.37
\]

Discounting is carried out in a similar manner for all remaining opinions.

The next operation on the FDV opinion is to translate the FDV opinion to a frame where it can be combined with other opinions to form a consensus about an appropriate state of a node’s antenna. Suppose the FDV and RNL opinions need to be combined. Before being combined, they need to be translated to a common cross product frame, for instance \( \Theta_{\text{FDV, RNL}} \times \Theta_{\text{RNL}} = \Theta_{\text{FDV, RNL}} \), where

\[
\Theta_{\text{FDV, RNL}} = \{(N - \text{SLOW}, N - \text{NEAR}), (N - \text{SLOW}, N - \text{FAR}), ... , (N - \text{FAST}, N - \text{FAR})\}
\]

Translation from \( \Theta_{\text{FDV}} \) to \( \Theta_{\text{FDV, RNL}} \) proceeds by associating the value of \( m_{\text{FDV}}(p), p \subseteq \Theta_{\text{FDV}} \) and attributing that value to the disjunction of all elements \( q \subseteq \Theta_{\text{FDV, RNL}} \) for which \( p \subseteq q \). Translating \( m_{\text{FDV}}(N - \text{SLOW}) = 0.6 \) gives the result \( m_{\text{FDV, RNL}}((N - \text{SLOW}, N - \text{NEAR}) \lor (N - \text{SLOW}, N - \text{FAR}) \lor ... \lor (N - \text{SLOW}, ...)) = 0.6 \). Translating, for instance, \( m_{\text{RNL}}(S - \text{NEAR}) = 0.8 \) to \( \Theta_{\text{FDV, RNL}} \) in a similar manner gives the result \( m_{\text{FDV, RNL}}((N - \text{SLOW}, S - \text{NEAR}) \lor (N - \text{FAST}, S - \text{NEAR}) \lor ... \lor (...) \lor (S - \text{NEAR})) = 0.8 \).

Once opinions are translated to a common frame, they are combined using Dempster’s Rule [2] that is defined as

\[
m_3(A_3) = (1 - k)^{-1} \sum_{A_1, A_2 \subseteq \Theta} m_1(A_1) \cdot m_2(A_2)
\]

where

\[
k = \sum_{A_1, A_2 \subseteq \Theta} m_1(A_1) \cdot m_2(A_2) \leq 1
\]

and \( k \) represents the total conflict in opinion between two sources. The role of \((1 - k)^{-1}\) above is to renormalize the degree to which two sources agree in proportion to the amount of conflict. Intuitively, this means even if two opinions are initially in strong disagreement, renormalization will convolve the amount of disagreement to the parts of their respective opinions in which they do agree no matter how minimal the amount of initial agreement. The above equation also means that Dempster’s Rule is undefined when two opinions are in total disagreement.

Translating and combining the opinions conveyed to \( \text{FDV, WDV, TG, and RNL} \) (commonly called Frame of Discernments (FODs)) we arrive at the following opinion over the \( \Theta_{\text{FDV, RNL, WDV, XYG}} \) that is abridged due to space limitations

\[
m_{\text{FDV, RNL, WDV, XYG}} = (\neg \text{SLOW}, \neg \text{NEAR}, \neg \text{SLOW}, \neg \text{NEAR} \lor \neg \text{SLOW}, \neg \text{NEAR}) = 0.27
\]

\[
m_{\text{FDV, RNL, WDV, XYG}} = (\neg \text{SLOW}, \neg \text{NEAR}, \neg \text{SLOW}, \neg \text{NEAR}) = 0.03
\]

\[
m_{\text{FDV, RNL, WDV, XYG}} = (\Theta_{\text{FDV, RNL, WDV, XYG}}) = 0.24
\]

The above consensus mass distribution is then translated to the Antenna Power FOD resulting in the following \( m_{\text{AP}} \)

\[
m_{\text{AP}}(\text{PowerUp}) = 0.3, \quad m_{\text{AP}}(\text{StandBy}) = 0.04, \quad m_{\text{AP}}(\text{PowerUp} \lor \text{StandBy}) = 0.42, \quad m_{\text{AP}}(\Theta_{\text{AP}}) = 0.24
\]

The \( m_{\text{AP}} \) result is then “interpreted” using the ER Interpretation operation that for each element in \( \Theta_{\text{AP}} \) produces an interval \( [\text{Spt, Pls}] \subseteq [0,1] \) and is defined as

\[
\text{Spt}(A) = \sum_{A \subset \Theta, p \in A} m(p) \text{ and } \text{Pls}(A) = 1 - \sum_{A \subset \Theta, p \in A} m(p)
\]

The interpretations of evidential intervals are as follows:

[0,0]: evidence suggests proposition is completely false
[1,1]: evidence suggests proposition is completely true
[n, 1]: evidence suggests proposition is partially true, for \( 0 < n < 1 \)
[0, n]: evidence suggests proposition is partially false, for \( 0 < n < 1 \)
[n, m]: evidence suggests proposition is partially true and partially false, for \( 0 < n < m < 1 \)
[0,1]: totally ignorant about the truth or falsity of the proposition

Interpreting the above \( m_{\text{AP}} \) results in the following evidential interpretation for the PowerUp, StandBy, and PowerDown propositions in \( \Theta_{\text{AP}} \).

\[
\text{EI}(\text{PowerUp}) = [0.3, 0.96], \quad \text{EI}(\text{StandBy}) = [0.04, 0.7], \quad \text{EI}(\text{PowerUp} \lor \text{StandBy}) = [0.8, 1.0]
\]

The EIs (Evidential Intervals) indicate that the evidence supports the belief, to a degree of 0.8, that the antenna for a node North or North-East of the fire should be placed in either Power Up or Stand By mode. There is also evidence, to a degree of 0.3, that the antenna should be Powered Up. The difference between the Plausibility and Support values in each EI is the degree of uncertainty about whether the Power Up, Stand By, or Power Down state of the antenna is most appropriate. Sensitivity analysis can help identify the additional information such that, if acquired, will help reduce uncertainty about the most appropriate antenna power state.
4. Results and Analysis

Every node in our simulations started with an initial energy of 2J and no restriction on the amount of data that can be sent to the Base Station. We have performed the NS2 simulations for a single cluster containing 7 nodes and each iteration represents 5 seconds in real time.

The data rate at which packets get transferred from cluster heads to the Base Station were extracted from the simulations. In addition, the energy used by each node to transmit the data to the Base Station was also calculated and extracted from the simulation. Since each node’s energy is not limitless, after a specific period of time nodes will no longer be able to receive or transmit data. The objective of an evidential approach is to delay this inevitable event as long as possible while maintaining acceptable purposefulness. In the Leach-C algorithm, the data to be transmitted is aggregated which helps to minimize traffic and hence energy consumption. Although data aggregation is not precluded in an ER approach, it was not considered in the work reported here.

In our ER approach to forest fire detection and monitoring, each node has sensors to provide some of the data about its immediate environment, such as temperature, humidity, sound (e.g., thunder), and elevation. Other sources of data such as wind direction and speed are obtained from a distributed set of devices such as anemometers, and so forth that are directly connected to a base station.

The ER approach proceeds by obtaining current environmental information and then using the analysis in Figure 4 to infer the state of each node’s antenna. In other words, data is propagated through an analysis to infer the state of node 1 in our seven nodes. Then data relevant for node 2 is used to infer its antenna state, and so forth for all seven nodes. Then the process repeats.

The energy efficiency was determined using the ER approach and compared with the LEACH-C algorithm. Power usage by the Base Station (BS) was not considered in efficiency assessments because in this simulation it has its own power source. By measuring the amount of data received at the Base station the effectiveness of detecting and monitoring forest fires in this data-dependent application can be assessed. A remote environment can be monitored or modeled more accurately as more data is received by the Base Station.

An ER-based simulation was completed for a duration of 150 seconds. The solid lines in each graph show actual simulation results. The dashed lines show hypothetical results based on projecting the observed results, i.e., simulated results, for the 150 second simulation period.

In the simulation, the initial environmental state is no fire, W-SW to SSW 5-10mph, fuel in NW corner of the seven nodes of interest is relatively dry. This state continues for 10 iterations or 55 seconds into the simulation. Then thunder is detected and the intensity and frequency of thunder increases over the next several iterations until a significant increase in temperature is observed, i.e., a small fire is detected. It spreads in a SW to SSW direction. The fire continues to progress in a SW to SSW direction and approximately at iteration 18, rain is detected. This state persists for the remaining duration of the simulation.

Figure 5 contains a plot of total data signals received at the BS over time. The figure shows that the ER approach sends much more data to the BS in the simulation time than LEACH-C. The reason is that data generated at each node is not aggregated at cluster heads and hence as a result more data is received at BS. In contrast, in many other protocols, the data transmitted to the BS is greatly reduced due to aggregation of signals at cluster heads.

Figure 6 contains a plot of the total number of data signals received at BS for a specified amount of energy. This graph shows that an ER approach is more efficient than
LEACH-C in that it provides the most data per unit of energy. An ER approach achieves this because energy is used only when necessary as compared to a fixed schedule.

Although in LEACH-C the BS has more aggregated information about the network, it does not consider surrounding environment conditions or the dynamics of the application domain when considering adjustments to the schedule.

Figure 7 shows the Number of nodes that remain alive during the simulation. Results from the graph show that ER has a greater overall network lifetime as compared to LEACH-C. An ER approach provides an ability to determine the most appropriate power state of a node’s antenna i.e. ON, OFF or STANDBY mode. Nodes are activated when there is a change in surrounding environment i.e. small fire detected with a wind velocity of 5-10mph. LEACH-C depends upon effective clustering to achieve energy efficiency and does not consider surrounding environmental conditions. An ER approach provides an ability to discover and deal with the vicinity impacting an antenna power state decision, which in turn improves the energy efficiency of the entire distributed sensor network.

Figure 8 shows total number of data signals received at the BS compared to the number of remaining functioning nodes. As seen from the previous graphs, the ER approach has higher energy efficiency compared to LEACH-C. An additional reason for this is that the LEACH-C algorithm requires more energy to send data to the BS due to the predefined schedule of when to activate nodes. Unnecessary power consumption occurs in the steady-state phase due to repetition of the same information with the previous slot in a fixed slot allotment frame. Although LEACH-C can measure data regularly, its energy consumption is much greater compared to an ER approach.

5. Conclusion

For the purpose of simulations we used Network Simulator-2 on a UNIX platform. The LEACH-C algorithm was used as a comparison against the proposed ER method. The reason for selecting LEACH-C is that it is currently the best performing algorithm with respect to energy efficiency. An improved improvement of 18% over the LEACH-C approach was observed when the ER approach is used. This appears to be a result of taking into consideration the surrounding environmental conditions and knowledge of the situational dynamics of the domain of application.

The evidential reasoning calculus was also introduced as a means to represent and integrate the bottom-up and domain knowledge necessary to infer a more optimal power state of DSN antennas. The context of our investigation was the task domain of detecting and monitoring the progress of forest fires.

The results involved a simulation of 7 nodes for 150 seconds. Future work will involve significantly expanding the number of nodes and complexity of DSNs.

![Time vs Nodes Alive](image1)

**Figure 7 Graph of simulation time vs # of nodes alive.**

![Data vs Nodes Alive](image2)

**Figure 8 Graph of data signals received vs # nodes alive.**

References


