

# Fuzzy Decision Making through Energy-aware and Utility Agents within Wireless Sensor Networks

S. Shen, G.M.P. O'Hare, M.J. O'Grady

*CLARITY: The Centre for Sensor Web Technologies, School of Computer Science & Informatics, University College Dublin, Belfield, Dublin 4, Ireland.*

+353-1-7162472

+353-1-2697262

{song.shen, gregory.ohare, michael.j.ogrady}@ucd.ie

<http://www.csi.ucd.ie>

*Abstract:* Multi-agent Systems (MAS) through their intrinsically distributed nature offer a promising software modelling and implementation framework for Wireless Sensor Network (WSN) applications. WSNs are characterised by limited resources from a computational and energy perspective; in addition, the integrity of the WSN coverage area may be compromised over the duration of the network's operational lifetime, as environmental effects amongst others take their toll. Thus a significant problem arises – how can an agent construct an accurate model of the prevailing situation in order that it can make effective decisions about future courses of action within these constraints? In this paper, one popular agent architecture, the BDI architecture, is examined from this perspective. In particular, the fundamental issue of belief generation within WSN constraints using classical reasoning augmented with a fuzzy component in a hybrid fashion is explored in terms of energy-awareness and utility.

*Keywords:* intelligent agents, BDI agents, energy-aware agents, utility agents, distributed decision-making, resource bounded reasoning, sensor data fusion

## 1 Introduction

A Wireless Sensor Network (WSN) consists of a suite of spatially distributed autonomous devices that incorporate a range of sensor components for monitoring arbitrary physical phenomena. Such networks have many potential applications, environmental monitoring being one obvious example. Such networks form an essential enabling technology for ubiquitous computing applications (Vasilakos and Pedrycz 2006), that is, applications that utilise components embedded within the very fabric of the environment in which the application is used. WSN applications have been the subject of significant study in academia and industry, and while their potential is immense, crucial systems engineering issues such as energy consumption and fault tolerance remain unresolved. However, the inherently distributed nature of WSNs suggests that the intelligent agent paradigm may encapsulate some of the essential concepts and constructs necessary for modelling and implementing applications, and deploying services on such networks.

Intelligent agents are a practical implementation of Distributed Artificial Intelligence (DAI) (O'Hare and Jennings 1996). Though their core characteristics of autonomy, mobility, reactivity, sociability and so on may vary according to the requirements of the application at hand, it is the reasoning model adopted that is their most distinguishing characteristic. This may range from a primitive model based on simple rules to one based on so-called mentalistic or cognitive concepts, a classic example being the Belief-Desire-Intention (BDI) architecture (Rao and Georgeff 1995). The BDI model represents an abstraction of human deliberation and is based on a theory of rational activity in the human cognition process. In a typical BDI architecture, the states of the agents are represented through three fundamental components: Beliefs, Desires and Intentions. Beliefs represent what the agents view about its environment at a given moment in

time. Desires represent the goals, objectives or tasks that agents seek to achieve. Intentions represent those desires that an agent is in a position to satisfy, at a given time. If a desire has successfully passed through a weighing function (in which the current belief set represents a key input parameter) and is subsequently chosen by the agent as an intention, it may be said that the agent has made a commitment to fulfill that intention at some future point in time. This intention is subsequently planned and executed.

Sensor networks exhibit a duality of function in the capture of data and its subsequent transport through the network to a back-end system; this data is usually routed via Base Stations (BSs) for analysis. Data gathering may be viewed as a combination of the following processes - sampling, data collection, local decision-making and fusion of local decisions. In the traditional client/server paradigm, these latter two processes occur at the server side. To minimise data traffic, and conserve energy, it would be desirable to undertake these processes on individual nodes in the WSN, provided of course that the computational cost from an energy and time perspective justified this approach. This issue, the intelligent utilization of energy in WSN nodes, is a formidable software engineering challenge in its own right. A further difficulty, and one of particular relevance to the ensuing discussion, concerns the nature of the belief generation process that comprises sampling, data gathering and theoretical reasoning. At any given time, a sensor by definition has access to only a sub-area of the measured physical phenomena in the total network coverage area; hence its knowledge of the prevailing situation is incomplete. However, transmitting raw data to the BS is costly in terms of both energy consumption and network bandwidth. An intrinsic ability to reason locally with incomplete data, augmented with an effective data gathering mechanism are therefore prerequisites for modelling the software layer of a WSN using an MAS. In this paper, the issue of belief generation for BDI agents within the inherent constraints of a WSN are explored, and a hybrid model based on deliberative and fuzzy reasoning proposed.

This paper is structured as follows: Section 2 examines related research in the areas of WSN data gathering, and examines developments in agent reasoning within resource bounded scenarios. Section 3 considers the energy-aware and utility-based agent model while Section 4 examines belief generation in a WSN scenario. Section 5 presents the results of some initial experiments on different data fusion strategies, and discusses the implications of these for belief generation. Finally, the paper is concluded.

## 2 Related Research

Multi-agent Systems (MAS) has demonstrated its aptness for the modelling of autonomous and distributed intelligent entities. BDI agents encapsulate an intelligent decision-making theory (Cohen and Levesque 1990; Bratman 1987) enabling them to operate within dynamic environments. In a typical BDI architecture, an agent is situated within its environment and executes autonomous actions so as to reach certain goals in a non-deterministic environment. BDI agents are rational, and represent an attractive software paradigm for autonomous electronic devices such as wireless sensor nodes. Such agents are normally associated with resource rich platforms and their computational requirements render it difficult to successfully deploy such agents on resource-bounded devices such as WSN nodes. However in recent years, the practical deployment of intelligent agents on resource-limited devices has been the subject of exploratory research, and a number of frameworks have been described in the literature. Well-known examples include 3APL-M (Koch et al. 2005), Agilla (Fok et al. 2005) and Agent Factory Micro Edition (AFME) (Muldoon et al. 2006). In the case of AFME, agents subscribe to the BDI paradigm. Documented implementations from the m-commerce (Keegan et al. 2008) and tourism domains (O'Grady et al. 2007) have also been published. Thus WSNs represent a new frontier for agent deployments, though significant challenges must be addressed before it can be claimed that intelligent agents represent a viable paradigm for WSN application development. While the

application domain is novel, one of the key issues that must be addressed is in fact a more acute case of a well known problem in Artificial Intelligence (AI) – bounded intelligence. Bounded intelligence (Goldman, Allen, and Zilberstein 2007; Schut and Wooldridge 2001; Breese and Fehling 1990) is one of the major concerns of AI as resources always fall short of the computational requirements intelligence demands. This is especially so when the intelligence model is applied to remote electronic devices such as mobile phones, or real-time systems (Zilberstein and Russell 1996). One solution to this might involve the adoption of meta-level reasoning which deals with the optimisation of the agent's performance by choosing and sequencing agent activities. In recent years, there has been growing interest in formal models of resource-bounded agents. Ho Ngoc (Ho Ngoc 2003) introduces algorithmic knowledge, a concept of knowledge which is suitable for establishing direct connections between knowledge and resources. His idea is to consider how much resources an agent requires to compute the answer to a particular query. Boella et al. (2005) seek to model the commonsense notion of intention in a system that is self-aware of its bounded-reasoning ability. Alechina and Logan (Alechina and Logan 2002) on the other hand consider the case for ascribing beliefs to resource-bounded agents. A number of researchers (Rao and Georgeff 1992; Rao and Georgeff 1995; Wooldridge 2000; Singh and Asher 1991) have developed logic theories involving multiple worlds and logical formalisms. In their definitions, each world is regarded as a combination of time and state expressions. The logic theories strengthen the usability of BDI agents and are viewed as critical compositions in the BDI family. However strict logic expression is neither effective enough nor sufficiently intuitive when applied to more complex applications where many competing goals and many aspects of these goals need to be considered. Trying to apply logic theory to a fuzzy process is a primary contributor to inefficiency. Furthermore, the study of modal logics fails to bring full axiomatization and it is not easily applicable to certain application practices. Contrasting approaches to the BDI model have been applied within the research literature. Case-Based Reasoning (CBR) (Corchado and Laza 2002; Olivia et al. 1999) is an experience-based approach and is in stark contrast to BDI. The reasoning of CBR is based on the reuse of past experiences or cases. Cases in CBR are represented by a tuple of problem, solution of the problem, and outcome. Outcome is the resulting state of the world after the solution is carried out and will be reused as a basis for future problems that present a certain similarity. Qualitative Decision Theory (QDT) (Boutilier 1994; Dastani et al. 2000; Pearl 1993), on the other hand, provides an alternative decision theoretic to traditional BDI logic. QDT is in essence a multi-level qualitative approach developed to reason about uncertainties, which are typically represented by a plausibility function. The key to QDT application is, however, how to remove the uncertainties or to calculate the possibilities in a broad sense, and in what way one is able to integrate experience with an agent model. Energy-aware and utility-based agents (Shen and O'Hare 2007) have been proposed to provide solutions to the modelling of distributed intelligence modelling for resource-bounded sensors. The authors view the matured BDI paradigm as an effective solution to such pervasive issues as load balancing, routing and distributed data processing. Before an agent can commence its reasoning cycle, it is necessary that it has access to up-to-date information. Thus effective data fusion is essential. Indeed this issue is a crucial research area in its own right in the WSN sphere (Yu and Varshney 1998; Hu and Blum 2001; Fok et al. 2005). Due to the tight relationship with the environment, the quantitative requirements in terms of latency and accuracy are strict and unforgiving in WSNs. Data fusion within WSNs was initially studied as an extension of traditional resource-rich sensor networks with a focus on the construction of fusion rules in terms of different approximations. In (Kumar et al. 2004), a data aggregation and consensus algorithm for object location and tracking applications deployed on WSNs is proposed. This consensus algorithm permits ad-hoc, in-network, group formation in response to a detected event. By reaching a consensus in the network, only a single message indicating the detected event needs to be forwarded to the tracking application at a base station, leading to significant savings in communication costs and

thus prolonging the operational life of the network. In this way, the network minimizes the need to transmit raw data. However, reaching this consensus requires additional computational overhead.

Przydatek and colleagues (Przydatek et al. 2003) propose a novel framework for secure information aggregation in large sensor networks. By constructing efficient random sampling mechanisms and interactive proofs, their solution enables the user to verify that the answer given by the aggregator is a good approximation of the true value even when the aggregator and a fraction of the sensor nodes are corrupted.

Chen et al. (2006) propose a meta-data-based data aggregation scheme for clustering in WSNs, where only one of the sensor nodes within the sensing range of an event in a cluster is selected to transmit the sensed data to the base station via meta data negotiation. Using this approach, they claim that their aggregation scheme is able to significantly reduce redundancy, and is effective in prolonging the network lifetime, as well as supporting scalable data aggregation.

From a WSN-based BDI agent perspective, it can be seen that data gathering and data fusion are essentially exercises in belief generation. In the following sections, this process is elaborated on while considering issues such as energy and utility. Moreover, it is intended to construct formal models for distributed data gathering and energy-aware adaptation, and incorporate these into a BDI agent structure.

Within this paper, data gathering for WSNs is viewed as the belief generation of an energy-aware and utility-based MAS. More specifically we wish to formalize the intelligence solutions such as distributed data gathering and energy-threshold-based adaptation under a refined BDI agent paradigm.

Before outlining a model for effective belief generation in sensor based BDI agents using fuzzy principles, it is instructive to reflect further on the critical issues of energy and utility, so as to understand their potential influence on the reasoning process.

### **3 Energy-aware and Utility-based Agents**

Different agent architectures may be applied to manage the inherent complexity of WSNs, according to the application domain in question. Indeed, the intelligence quota required may differ at various levels in the WSN hierarchy. To illustrate the issues involved, one example of a network is now briefly considered.

#### **3.1 Agent Architecture**

An arbitrary WSN may be divided into a number of WSN subsets - each of which consists of a group of sensor nodes and at least one BS. How these subnets are defined can vary but the selective use of clustering techniques offers one potential solution (Younis et al. 2006). At a higher level, it is easy to envisage an additional layer that manages the BS level. Depending on the complexity of the network, additional layers could be added. However, each layer increases the computational resources available to the application. For discussion purposes, the simplest case is considered – a two level architecture.

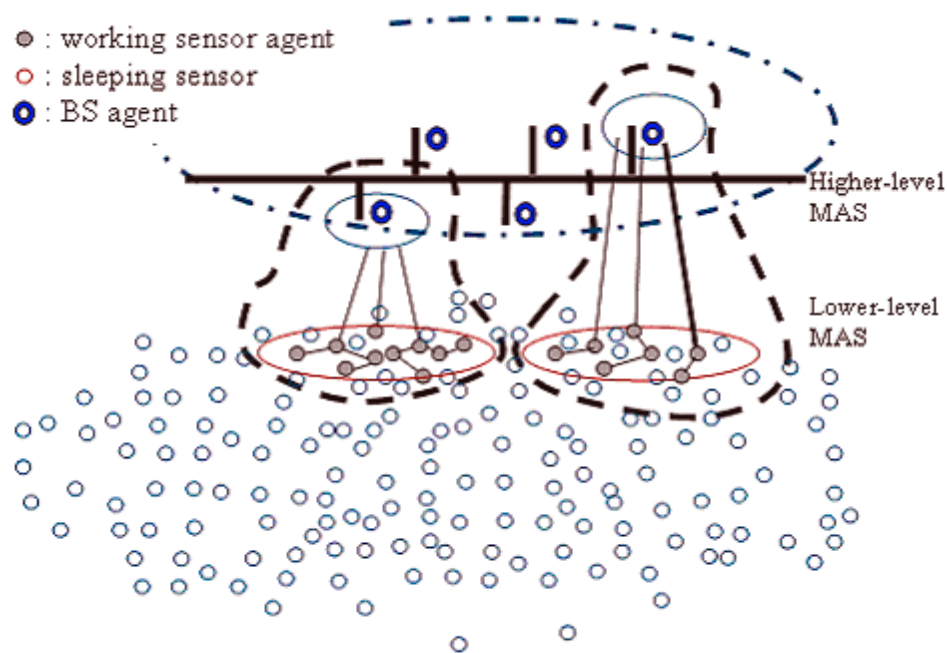


Fig. 1 A two-level MAS structure for WSNs

Within this architecture, a two-level BDI multi-agent system is proposed as outlined in Fig. 1. The higher-level MAS consists of a number of WSN subsets. This MAS is comprised of resource-rich members, and may be regarded as constituting a classic BDI MAS. Within this MAS, information may be freely exchanged without regard to cost constraints. Indeed, decisions that affect the entire network may be made at this level. The beliefs that inform these decisions are those propagated from the lower-level MAS, that is, the individual sensors, via their BSs. The lower-level MAS consists of a BS agent and a number of sensor agents. At this level, agents must be energy-aware; however, this not exclude being deliberative. Indeed, both BS agents and sensor agents are regarded as deliberative agents, although their deliberation abilities differ. Sensor agents, embedded within their environment, are responsible for collecting measured data about arbitrary physical phenomena - a process triggered either by an internal timer or an external event. Any information captured is pre-processed and encoded before being dispatched to the BS agent within the subnet, through an ad hoc route. Sensor agents also participate in relaying data to cooperatively accomplish the data aggregation mission of the subnet. Such agents may undergo the sleep-idle-active cycle repeatedly during its lifetime at the coordination of the MAS to which it is affiliated.

BS agents, in contrast, are resource-rich and have more responsibilities. These include:

- receiving raw data from all active sensor nodes within the subset;
- acting as a coordination center, by instructing certain sensor nodes to switch among sleeping, idle or active states as necessary;
- analyzing and exploring the correlation amongst data generated from sensor nodes, eliminating excessive redundancy in raw data, and quantifying the fidelity of captured information;
- generating a comprehensive global belief set for the entire WSN.

The objective of a BS agent is to monitor the environment in a cost effective manner where cost is measured in terms of power depletion. To do this, it must undertake certain tasks such as delegating certain functions to lower-level MASs, monitoring the topology of the network and managing load balancing to mention but a few. Within a typical WSN, a BS agent acts as a focal point of the network where information is fused and where decisions that may have global ramifications are made. Each BS agent in effect functions as a mediator between the two MAS levels. The agent members of the higher-level MAS are peer-to-peer, while those of the lower-level MAS, due to the differential in capability and vision, may operate in either a peer-to-peer or client-server fashion.

Due to the inherent characteristics of wireless connections and the limited energy resources, the lower-level MAS is restricted in its ability to reason. In fact, the communication capability for relaying transmissions, in which most sensor agents exchange messages with the BS indirectly, is limited. In addition, in order to save energy, sensor agents cannot be awake all of the time.

Therefore, an impromptu lower-level MAS consists of a number of selected nodes. These sensor nodes are normally, but not necessarily, homogenous. For a dense WSN, the dynamic lower-level MAS is typically only a subset of all available sensor nodes capable of performing a specific service, while the remaining sensor nodes are instructed to sleep so as to save energy. The more the number of connected sensor agents, the greater confidence the MAS has in its belief set, but the higher the power consumption. A lesser number nodes decreases the confidence that can be assigned to the veracity of the belief set while reducing the power consumption. Though this has implications for network longevity, it also has implications for the agent's deliberative or reasoning function.

### **3.2 Reasoning in the BDI Paradigm**

In a WSN scenario, there are two categories of reasoning that agents must be endowed with:

- practical reasoning which reasons toward actions;
- theoretical reasoning which reasons toward beliefs.

#### *3.2.1 Practical Reasoning*

For sensor agents, a critical element in their practical reasoning involves trade-offs that must be undertaken in near real-time conditions. To reconcile the conflicting goals of network operational longevity and performance, the agent must be inherently rational. Such agents must be capable of coordination, be sensitive to broad contextual changes, and be adaptive to changing network operating conditions. Ideally, such agents would enable energy-aware data collection and autonomic behaviors (Shen and O'Hare 2007) in the WSN. Such requirements demand a level of sophistication that BDI agents could deliver.

#### *3.2.2 Theoretical Reasoning*

The second category of agent reasoning concerns decisions on belief generation. Recall that the predominant objective of a WSN is to collect environmental information; this information forms the basis for an agent to construct its belief set. Whatever the preceding data collection mechanism is, the data collected needs to be transformed into beliefs through theoretical reasoning as is named within BDI agent paradigm. Due to the uncertainties caused by the limitation of the agent's perception abilities and environmental dynamics, beliefs can be considered as fuzzy (Zadeh 1965); indeed, theoretical reasoning based on fuzzy sets has been shown to be effective when dealing with uncertain environments (Luo et al. 2003).

The belief generation of a WSN based agent may also be viewed as an inherently fuzzy-based theoretical reasoning process. The term fuzzy related to an individual problem which can be repeatedly sub-divided until a sub-level is reached where the sub-problems are immediately solvable. In contrast, humans may not always take this approach; rather, they prefer to make

decisions at a higher level where the sub-problems may not be immediately clear to them. Ordinarily, goals are selected by weighing them according to particular though fuzzy criteria, for example perceived cost, time, quality and accessibility. Consider the identification of a holiday destination. Factors such as cost, duration, ease of access (transportation), and anticipated enjoyment (quality of the result) are included in the selection process. For agents to effectively function in WSN scenarios, it is essential that they be equipped to handle uncertain or fuzzy data. WSNs are inherently noisy and lossy environments which results in data that are uncertain or fuzzy. In the case of BDI agents, it is crucial that their belief formation logic can handle some uncertainty. Thus in the next section, a prerequisite to effective belief formation is examined, namely a fuzzy-set-based data gathering scheme.

## 4 Belief Generation in a Fuzzy Context

While data gathering is a general term for collecting data from multiple sensors, the terms data aggregation and data fusion both refer to the analysis and interpretation of the data. Though these terms are commonly used, there is not a complete consensus as to their meaning (Kalpakis et al. 2003; Przydatek et al. 2003). Thus, as far as this discussion is concerned, data aggregation, data gathering and data fusion all refer to the combination of multiple sensor data into one representation or control action. For a perception-rich sensor network, data gathering is the critical enabler of belief generation. Without losing generality, we assume that belief generation is separable into mathematical processing of individual local decisions from constituent sensor agents. Thus, the data gathering of a WSN is separated into the following processes: sampling, local decision making, data collection and belief generation.

Data fusion is generally categorized into three levels, namely raw data fusion, feature fusion and decision fusion (Dasarthy 1994; Chamberland and Veeravalli 2003):

- Raw data fusion constitutes low level fusion, which combines several sources of raw data in order to provide synthesised information. The dataflow of such a raw data fusion network is the raw data itself.
- Feature fusion combines relevant features extracted from the raw data. Those features may be identified from several raw data sources or from a portion of the raw data itself. The dataflow of a feature fusion network is the feature data.
- Decision fusion is a high level fusion of data, which combines decisions coming from disparate intelligent sensor nodes. Methods of decision fusion include voting methods, statistical methods, fuzzy logic based methods, and so forth. The dataflow of a decision fusion network is the local decision.

When BDI agents are considered in a WSN context, it can be seen that in generating their beliefs, a BDI agent is essentially engaging in an exercise of data fusion or data aggregation. Following belief generation, an agent must then make a number of decisions that will dictate its future course of action. Normally in a WSN, this would be centralised with all the data passing up the hierarchy. However, distributed decision-making is a more intuitive model from both a WSN and MAS perspective. Given the resource limitations of the current generation of wireless sensor nodes, enabling the strong interaction necessary for distributed decision making is almost impossible. However, future developments in WSN node hardware are likely to reduce the impact of resource limitation.

Within this paper, data gathering is considered synonymous with belief generation, which is achieved based on local decisions from sensors and the fusion of local decisions at the MAS level. Such a solution is based on the assumption that the sensor MAS decision-making is

decomposable onto local decision-making of WSN nodes. Such local decisions can be derived either selectively (Qi et al. 2002) or unselectively. By the adoption of local decision-making and a decision-level fusion mechanism, the MAS can avoid excessive exchange of raw data. A model to affect local decision making is considered next.

#### 4.1 Sampling and Local Decision-making

The noise of sensor  $i$ ,  $n_i$ , follows the Gaussian distribution:

$$(1) \quad n_i \sim N(0,1)$$

The binary hypothesis ( $H_1, H_0$ ) testing can be expressed as:

$$(2) \quad \begin{matrix} (H_1) \\ (H_0) \end{matrix} : r_i = s_i + n_i$$

where  $r_i$  is the received signal known as the sample, and  $s_i$  the signal amplitude. The local decision  $d_i$  of each sensor can thus be denoted as:

$$(3) \quad d_i \rightarrow \begin{cases} 0 & \text{if } H_0 \text{ selected;} \\ 1 & \text{otherwise.} \end{cases}$$

Within the WSN coverage area  $A$ , the target signal decays according to the following attenuation model:

$$(4) \quad s_i = \sqrt{P / (1 + \alpha X_i^v)}$$

where  $P$  is the central power strength,  $X_i$  is the distance between the target and an individual sensor node, and without losing generality,  $v$  is an exponent,  $2 \leq v \leq 3$ . Using the same threshold  $\tau$  to make a binary decision, the false positive rate  $p_f$  can be determined from the following equation:

$$(5) \quad p_f = \int_{\tau}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$

The correct decision rate  $p_{d_i}$  can be determined from:

$$(6) \quad p_{d_i} = \int_{\tau}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(t-s_i)^2}{2}} dt$$

The Chair-Varshney rule (Dasarthy 1994) could be considered as the optimal decision fusion rule:

$$\Lambda = \sum_{i \in A} \left[ d_i \ln \frac{p_{d_i}}{p_{f_i}} + (1 - d_i) \ln \frac{1 - p_{d_i}}{1 - p_{f_i}} \right] \quad (7)$$

It is difficult to quantify  $p_{d_i}$  since it is determined by both distance and signal amplitude. Equation 7 can only be simplified under some further assumptions (Niu and Varshney 2005; Niu et al.

2004). For example if we set  $p_{d_i} = p_d, p_{f_i} = p_f, \forall i \in A$ , then Equation 7 can be simplified to:

$$\Lambda = \sum_{i \in A} d_i \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \tau \quad (8)$$

In effect, Equation 8 states that if each sensor is treated as equal, then the decision rule regresses into a simple voting mechanism.

## 4.2 Data Collection

Data, either samples or local decisions, must be collected for network-level decision-making so as to generate beliefs. Different methods can be adopted for data collection.

One genre of data collection is the client/server paradigm, where constituent sensor nodes are required to sample and transmit during their lifetime. This can be viewed as indiscriminate data collection which is patently uneconomic because sensor nodes involved are not necessarily generating useful samples all through their lifetime. However it is easy to implement, and the samples collected covers the topography of the WSN.

Duplicate sampling is a waste of both energy and bandwidth. From this perspective, the second genre - selective sampling is necessary. Mobile-agent-based data collection (Qi et al. 2002) is one intelligent solution to sampling whereby agents can migrate from one sensor node to another, according to sampling requirements.

## 4.3 Belief Generation through Agent Theoretical Reasoning

Belief generation of a WSN subset is based on the accumulated data, whether it is collected by all nodes or partial sensor nodes or mobile agents. Centralized decision-making is usually adopted for the WSNs where all information passes up the hierarchy to the BS network (Niu et al. 2004; Chamberland and Veeravalli 2003), or even further up the hierarchy to a fixed workstation. A key limitation of such decision-making is that it can incur a significant penalty cost in terms of time and power to propagate the fused data back to the BSs. However, centralization is necessary because sensor nodes are critically resource-bounded, and they are limited in what they can perceive. Hence, in conventional WSNs, the primary purpose of the data fusion process is to supply a fused picture to the decision-makers at the top of the hierarchy. However, there are a number of disadvantages associated with a centralized architecture:

- Fusion of data expends significant communications bandwidth;

- Latency is inevitable since the fusion of data through relayed communication is costly in terms of time;
- Node failure, which is common to WSNs, could cause a local failure in the network.

The solutions to these problems are straightforward. Besides an effective topology modelling and management scheme, for example AToM (Shen et al. 2006), it is necessary to minimize mass data transmission in order to decrease both the required transmission bandwidth and the transmission latency. In a loosely connected network, remote sensor nodes have to make local decisions, rather than pushing raw data to a remote BS. For example, in a large-scale fire monitoring network, the WSN nodes should be capable of expediting sampling when the threat from a potential fire is identified, as well as adopting other strategies that would increase responsiveness, for example, adaptive scheduling (Ruzzelli et al. 2005). Nodes should also be capable of proactively restoring original operating parameters when conditions return to normal. Such decision-making necessitates an ability to cooperate. Conceptually, the WSN nodes may be regarded as deliberative agents capable of making autonomous decisions both in isolation and in cooperation with other agents. For many WSN-based applications, it is practical to make decisions based upon node-based partial decisions. In the case of BDI agents, an effective mechanism for belief generation must be developed. Such a belief-generation mechanism must adopt elements of both centralized decision-making and distributed decision-making. Specifically, the local partial decisions are made by individual WSN nodes while belief generation is made centrally at the BS. This reflects the capability difference between BS agents and sensor agents (dictated by hardware considerations), and the distributed characteristics of a WSN. In this way, the WSN nodes, which possess certain calculation abilities, share some reasoning tasks locally, and therefore reduce the need for data transmission on the network.

Let  $D^k = \{d_1 d_2 d_3 \dots d_M\}$  be the possible decision of node  $k$  based on a group of  $N$  neighbouring nodes  $S^k = \{s_1 s_2 s_3 \dots s_N\}$  and  $M$  aspects. Node  $k$  can either be a WSN node or a BS. The relationship of  $D_k$  and  $S_k$  is defined as a fuzzy set of  $D_k \times S_k$ . Suppose vector  $T = \{t_1 t_2 t_3 \dots t_N\}$  is a membership function on domain  $S_k$ , representing the believability of WSN nodes in the decisions, then Equation 9 outputs the fuzzy-set-based transform of  $T$ . Vector  $U$  represents a membership function on domain  $D_k$ . The physical meaning of Equation 9 is that decisions are decided by the fuzzy transform of the membership of each local decisions and its believability:

$$(9) \quad U = R_{D^k \times S^k} \circ T$$

where  $\circ$  is a fuzzy operator, and  $R_{D^k \times S^k}$  is a fuzzy membership function on relationship. As the result of the fuzzy transform,  $U$  can be further denoted as:

$$(10) \quad U = \{u_1/d_1, u_2/d_2, u_3/d_3, \dots, u_M/d_M\}$$

$$(11) \quad u_i = \bigcirc_{k=1}^N \mu_{ki} \circ t_k$$

where  $\bigcirc$  is a fusion operation. can be “ $\Sigma$ ”, “ $\max\{\}$ ”, or “ $\min\{\}$ ”.

During a belief generation process, any element  $\mu_{ij}$  of the relationship matrix  $R_{D \times S}$  denotes the possibility of getting decision  $j$  from sensor  $i$ . Of course, not all data are indispensable for decision-making purposes. When an element is missing, the corresponding coefficient is set to 0. The membership function is:

$$R_{D^k \times S^k} = \begin{bmatrix} \mu_{11} & \mu_{12} & \dots & \mu_{1N} \\ \mu_{21} & \mu_{22} & & \mu_{2N} \\ \dots & & & \\ \mu_{M1} & \mu_{M2} & & \mu_{MN} \end{bmatrix} \quad (12)$$

$R_{D \times S}$  can be expressed in different ways. For example,

$$\mu_{ij} = \mu_{ij} / \text{Max}(\mu_{1j}, \mu_{2j}, \dots, \mu_{Mj}) \quad (13)$$

If we adopt  $\Sigma=O, \circ = \times$ , then the fuzzy decision matrix will reduce to a normal weighted decision matrix:

$$U = W \cdot R_{D^k \times S^k} \cdot T \quad (14)$$

Therefore the belief generation becomes the solution of a weighted decision matrix. If the final decision-making could be linearly processed from partial decisions, then  $U$  may be considered as:

$$U = \sum_{i=1}^M w_i u_i \quad (15)$$

#### 4.4 Cost Awareness and Adaptation

Having examined conventional belief generation, it now necessary to consider the cost in terms of energy and time associated with any proposed course of action. Resource-bounded reasoning is central to preserving operational longevity within WSNs devoid of consideration of computational and operational constraints. Implicit within the spectrum of action that an agent is capable of are those necessary for the generation and maintenance of beliefs. Finally, the issue of adherence to a time limit for decision making must be considered.

##### 4.4.1 Energy Cost and Time Cost

Time awareness helps agents to control the timing of their atomic processes in order to prolong the network's operational lifetime. In the agent's control algorithm, it may be accommodated in the form of a threshold value. In contrast, energy is best considered through a utility function. Energy awareness of a WSN node may be achieved in two ways. The first is to obtain an estimation based upon experimental data on message transmission and routine operation, together with battery specifications. A second strategy to achieve energy awareness is to harness some specific sensor nodes which themselves have embedded sensors for detecting and monitoring energy levels. Depending on the application at hand, a qualitative or quantitative approach may be adopted. Either way, an agent can and must factor energy into its deliberations.

Awareness of status and workload is also a prerequisite for the effective management of the central decision making control loop. Status awareness is achieved by periodic revision of beliefs thus ensuring the agent's environmental model is always valid. This validity is contingent upon an appropriate frequency sampling together with a sufficiently low latency of belief generation.

However, it is also necessary to quantify the decision making process itself in terms of time and energy.

This assumption that the sensor MAS decision-making is decomposable helps derive the cost of a deliberation function, which is divided into some partial decisions of local sensor agents. Within the following analysis, we denote T and E separately as time cost and energy cost respectively. We denote superscript l, d, and t to represent local decisions, belief generation at a BS, and the transmission of local data respectively. Finally we denote subscript i as WSN node i. For example

$$T_i^t \quad (i \in \{1, N\})$$

denotes the time cost of transmitting the sample data or partial decision from local node i to the BS.

The time cost of decision-making of a WSN is attainable, given the above assumptions. For each decision-making episode, there exists three major time costs: the time cost of local decisions, the time cost of belief generation at a BS, and the time cost of the transmission of local data. The

$$\sum_{i=1}^N T_i^t$$

total communication time cost is  $\sum_{i=1}^N T_i^t$ . However, if the communication tasks are well sequenced within its channel, the minimum communication time cost is close to

$$\max \{T_i^t\}, i = 1, 2, \dots, N$$

$$\sum_{i=1}^N T_i^l$$

The cost of local decisions can either be  $\sum_{i=1}^N T_i^l$  if the local decision is made at the BS, or be negligible if the local decision is made at each sensor involved in a parallel manner. If we simplify belief generation into separable mathematical processing of individual aspects of individual local decisions, then the time cost of the belief generation can be considered as proportional to the number of aspects for evaluation M and N. Formally,

$$\sum T_i^d = M \cdot N \cdot t_1$$

, where M is the number of aspects for evaluation,  $t_1$  is the time cost of mathematical calculation on each aspect of each agent, which can be derived from algorithm analysis or experiments. Since the local decision time is much shorter than transmission time, for belief generation of homogeneous sensor nodes, the entire decision time cost  $\Gamma$  is

$$\Gamma = \max \{T_i^t + T_i^l\} + \sum_{i=1}^N (T_i^d) = (L-1) \cdot t_0 + N \cdot M \cdot t_1 + t_2$$

(16)

where  $t_0$  is the time cost for each hop,  $t_2$  is the time cost for local decision-making;  $t_0$  and  $t_1$  can be derived from experiments. For belief generation on raw data level, the entire decision time cost  $\Gamma$  is:

$$\Gamma = \max \{T_i^t\} + \sum_{i=1}^N (T_i^l + T_i^d) = (L-1) \cdot t_0' + N \cdot M \cdot t_1 + N \cdot t_2$$

(17)

Where we adopt a new hopping time cost  $t_0'$  to clarify its difference to  $t_0$ . In fact, raw data level belief generation costs much more than decision level, since all its raw data samples need to be transmitted to the BS. In addition, for raw data level belief generation, the local decisions are made by the BS. Therefore, the total time cost for local decision-making is  $N \cdot t_2$ .

Let  $E_t$  be the energy cost to transmit a piece of a sample message to its neighbors, and  $E_r$  be the energy cost to receive this message. If a piece of a message is sent through H hops and finally reaches the BS, then the hopping energy expense  $E_H$  is expressed approximately as (Rabiner et al. 2000):

$$E_H = H \cdot E_t + (H-1) \cdot E_r$$

(18)

So, in general, the minimum total energy cost of one belief revision cycle,  $E$ , is expressed as:

$$(19) \quad E = \sum_{k=1}^L \left( (N - \sum_{J=1}^{k-1} (N_J)) \cdot E_t + (N - \sum_{J=1}^k (N_J)) \cdot E_r \right)$$

where  $L$  is the total number of energy levels involved, and  $N_J (J \in \{1, N\})$  is the number of sensors on energy level  $J$ . At the end of clustering (forming of WSN subsets),  $N_J$  can be a concrete value. For a network where sensor nodes are evenly distributed on each energy level, Equation 19 can be further simplified as:

$$(20) \quad E = \frac{L+1}{2} N \cdot E_t + \frac{L-1}{2} N \cdot E_r.$$

Under the simplification adopted within this section, it is possible to deduce adaptation of WSN subnets informed by issues of energy consumption. This adaptation process is now described.

#### 4.4.2 Adaptation

Adaptation to a time limit is critical for real-time decision-making. In terms of an energy-aware and utility-based BDI agent network, adaptation is achieved based upon an awareness of cost and status, as well as the regulation of the volume of the decision matrix (see Equation 12).

Within the proposed model, applications can take advantage of parameterizable algorithms in re-configurable hardware. From Equation 16, it can further be deduced that in order for decision-making to occur within time limit  $\Gamma_0$ , the number of sensor agents needs to be adjusted to  $\Gamma_0$

$$(21) \quad N = \frac{\Gamma_0 - (L-1) \cdot t_0 + t_2}{M t_1}$$

Further improvements can also be made by implementing the calculation using a different number of selective algorithm aspects, thereby adapting to the available computation time. Similarly, from Equation 20, the number of sensor agents can be deduced in order to enable decision-making with minimum energy cost  $E_0$  under the equal-distribution assumption:

$$(22) \quad N = E_0 / \left( \frac{L+1}{2} \cdot E_t + \frac{L-1}{2} \cdot E_r \right)$$

In practical situations, sensor messages may be routed in a sub-optimum manner. Therefore, the real energy cost and time cost may exceed  $E_0$  and  $\Gamma_0$ . However, the adaptation of Equations 21 and 22 are important in guiding the design of the perception of the environment within certain thresholds of time or energy consumption overhead.

#### 4.4.3 Learning of Weights

The contributions of WSN nodes involved in the decision making process are typically neither equal nor static. When a WSN is deployed to monitor some fixed location, the corresponding decision weights can adapt to reasoning results through a simple learning process. For the  $k^{\text{th}}$  round of decision-making, each believability is derived from:  $\chi$

$$(23) \quad \chi_i(k) = S_i(k) / \left( \sum_{j=1}^M S_j(k) \right)$$

where  $S_i(k)$  is the accumulated number of correct reports of node  $i$ . The *a priori weight*  $S_i(k-1)$  and *a posteriori weight*  $S_i(k)$  satisfy

$$(24) \quad S_i(k) \leftarrow \begin{cases} (S_i(k-1) + 1) & \text{if } U_j \text{ and } \mu_{ij} \text{ are coincident;} \\ S_i(k-1) & \text{otherwise.} \end{cases}$$

By learning weights, a WSN can opportunistically decide the contributions of each node involved, thereby facilitating belief revision.

## 5 Experimental Analysis

In order to exercise the theoretical model and subject it to the rigors of a practical environment, an initial implementation has been undertaken. Initial experimental work now demonstrates how belief generation can be achieved on Berkeley motes using the theoretical reasoning model presented.

### 5.1 Experimental Design

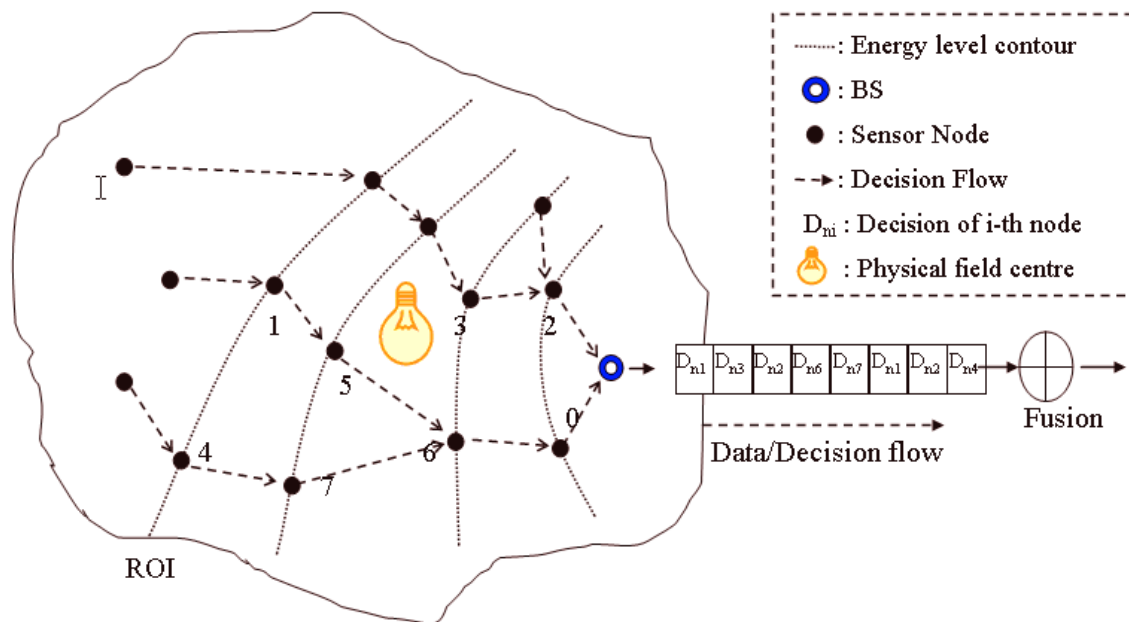


Fig. 2 Schematic view of a simple monitoring scenario

Initial work is undertaken based on a simple monitoring scenario demonstrated in Fig. 2, where an agent monitors a physical field within a region of interest (ROI). In essence, an outbreak of fire is being simulated. The switching on and off of a 100w reading lamp (which is placed directly on the top of the sensor nodes) is the event to be monitored. Experiments were conducted upon Berkeley motes that work at a baud rate of 57600 and which run TinyOS. The experiments were carried out with the eight sensor nodes available to us, and this WSN was commissioned to monitor a simulated fire from outbreak to extinction. Each WSN

node continuously keeps outputting its partial decision at a 20 second interval to the BS, which is responsible for the fusion of the partial decisions and the final synthesis decision. Because of their geographic divergence, sensors make different contributions to the decision-making. In order to identify the differing contributions, different weights can be associated with each WSN node. Furthermore a learning process could be commissioned to dynamically set a weight for each node involved. However for simplicity, our experiments merely default to equal weights. These events are similar to fire monitoring because they bring fundamental physical changes on both temperature and illumination within the region of interest. In fact this series of mote-based experiments can be viewed as a simulation of belief generation of such cases as fire monitoring, where the switching on/off of the lamp represents the starting/ending of fire. The motes are arranged within the physical field, converging in the centre of the field. A remote base station can only be directly accessed through those sensors which are situated on the lowest energy level (in the case of Fig. 2, sensors 2 and 0). All messages from the other nodes need to hop one or several times to reach the BS. The experiments are based on the following general assumptions:

- there exists one fixed energy-rich BS and a number of sensor nodes that are stationary, homogeneous and energy constrained;
- the BS is located at some distance from the sensor nodes and the communication between a sensor node and the base station is expensive.

The major purpose of the sensor network is to collect data through sensing at a fixed rate and convey it to the BS. Lots of samples need to be filtered in order to eliminate or repeat irrelevant measurements and these are then processed locally into meaningful information. The sensors are autonomously operating within the region of interest and can be interrupted by such events as a timed detection of a certain physical measurement, or perhaps receipt of a message. Therefore the major behaviors of the sensors can be identified as sampling, local decision-making, message (local decisions) collection and belief generation. For such a WSN-based monitoring system, decision time, fusion error, energy consumption and intelligence level are considered as the most crucial indexes. The mote-based experiments can be divided into the following four basic processes - sampling, local decision-making, collection of message, as well as belief generation. Among these processes, the local decision-making and belief generation processes are of particular interest.

### *5.1.1 Sampling*

For our purposes, just two of a range of the mote sensing capabilities are sampled – light and temperature. These samples are then used for subsequent local decision making.

### *5.1.2 Local Decision Making*

When the lamp is off, both the temperature and light readings are less than 0x200h. According to the experiments, both readings will increase to greater than 0x500h for all involved sensors when the lamp is switched on. Within this experiment, the exact values of sample physical readings are not that important. Rather, the switching on/off of the lamp is simple example that demonstrates the effects of our belief generation mechanism, which constitutes sensor-level local decisions and a subset-level fusion of these local decisions. Therefore the thresholds of local decision-making on light and temperature are set to 0380h, which is the middle point of 0x200h and 0x500h.

### *5.1.3. Collection of Messages*

Message sending occurs before partial decisions are made when raw-data level or feature level belief generation are activated. However for decision-level belief generation, the process occurs after the partial decision has been made.

All experiments are based on Berkeley motes that operate at a baud rate 57600 and use active messaging. Each message (e.g. FF FF 02 7D 1A 03 00 01 00 00 00 11 11 11 11) received at the BS represents a partial local decision, and is composed of 4 bytes destination address (BS address FF FF), 2 bytes handle id, 2 bytes group id, 2 bytes message length, 4 bytes source address, 4 bytes counter, 4 bytes channel id and 2×4 bytes data area. The experiments were carried out with all 8 sensor nodes deployed to monitor a lamp. Each sensor keeps outputting its local decision at 20 second intervals to the BS, which is responsible for the fusion of the local decisions and for belief generation. The experiments were carried out on a limited space; hence the distance between any two members of the WSN subset is actually within direct communication distance.

#### 5.1.4 Belief Generation

Within a raw data level belief-generation event, raw data are fused in the BS without processing, after which the beliefs are generated. Within a decision level belief-generation, on the other hand, only local decisions are fused. This experiment works at the decision-level, and belief-generation is made based on all the local decisions collated by the BS. The only difference between decision-level and raw-data level is the content and the length of message flow.

#### 5.1.5 Decision Rules

```
[1] BELIEF(is(Fusion, Low)) =>COMMIT(Self, Now, Sample);
[2] BELIEF(is(Fusion, Medium)) =>COMMIT(Self, Now, Speed);
[3] BELIEF(is(Fusion, High)) =>COMMIT(Self, Now, Report);
[4] BELIEF(is(Fusion, High)) & BELIEF(is(Acceleration, High)) =>
      COMMIT(Self, Now, Warn);
[5] BELIEF(is(Fusion, High)) & BELIEF(is(Acceleration, High)) =>
      COMMIT(Self, Now, Warn);
```

Fig. 3 Commitment rules utilized by the agents

A WSN can normally be viewed as a perception rich and action-less network which is not a fully functional system. However, if we view it independently, then ‘warning’ and ‘reporting’ could be viewed as its actions. The example commitment rules of the agent on belief-generation are listed within Fig. 3. These rules could be translated through the correspondence of agent actions with the agent’s beliefs concerning the status of the lamp. When the belief is normal, the agent will continue routine sampling; when the fusion output gets higher than a medium level, the sensors will increase the sampling rate (at the request of the BS or autonomously) to provide more environmental data; when the fusion output reaches high, the system will issue a warning; when both fusion output and its acceleration are high, the agent will not only issue a warning, but also report on certain public channels. All the rules are expressed in Agent Factory commitment rule format. Note that only commitment rules 1, 3 and 4 are executed with these experiments.

## 5.2 Experimental Results

Four sets of experiments were designed and undertaken in order to investigate the applicability of the models outlined in Section 4. The first set investigates the effect of local partial decisions on belief generation. This is followed by a suite of experiments that seek to quantify the effects of routing, time and energy cost, and to understand the implications of these for a belief generation strategy.

To simplify local processing, Equation 14 is applied to make the partial decision of a sensor. The contribution of each sensor is decided by both light and temperature aspects

$$\mathbf{u}_j = \begin{bmatrix} \mu_{00} & \mu_{01} \\ \mu_{10} & \mu_{11} \end{bmatrix} \begin{bmatrix} \chi_0 \\ \chi_1 \end{bmatrix}$$

. In this case, light and temperature aspects are equally taken into account by a certain threshold to simplify the processing of local decision-making. Thus

$$\begin{bmatrix} \mu_{00} & \mu_{01} \\ \mu_{10} & \mu_{11} \end{bmatrix} \text{ can be standardized into } \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}. \text{ Therefore, } \mathbf{u}_j = \sum_{i=1}^2 0.5 \cdot \mu_{ij},$$

where  $j=1, 2, \dots, 8$ . When both sensors report 'high'  $\mu_{ij}$  values, the output of the partial decision will be decided by:

$$(25) \quad \mathbf{d}_j \rightarrow \begin{cases} 0 & \text{if } \mathbf{u}_j \leq 0.5; \\ 0.125 & \text{otherwise.} \end{cases}$$

Equations 10 and 11 are then applied to the belief-generation of the energy-aware agent. In this case, it is assumed that  $\Sigma=0$ ,  $\circ = \times$ . It is also assumed that the partial decisions are independent to each other and have the same weights. Thus for an N-sensor network, the decision matrix is

$$\text{simplified to } \mathbf{U} = \sum_{i=1}^N \mathbf{d}_i, \text{ while the belief is generated based on the following rule:}$$

$$(26) \quad \text{Belief} \rightarrow \begin{cases} \text{is(Fusion, Low)} & \text{if } U < 0.5; \\ \text{is(Fusion, High)} & \text{otherwise.} \end{cases}$$

Within these experiments, the total number of sensor nodes is 8, hence . If four nodes are contributing a 'fire' partial decision,  $U=4 \cdot 0+4 \cdot 0.125 = 0.5$ , which means the possibility of 'fire' is 50%. In this experiment, the warning threshold is set to 50% possibility. Therefore, there will be a 'fire' warning when four nodes reported 'fire' partial decisions.

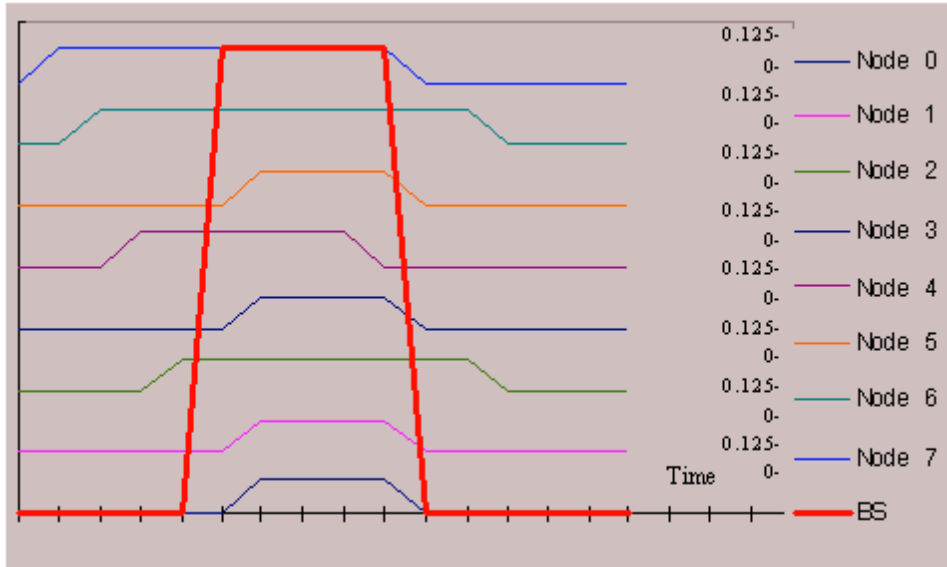


Fig. 4 Relationship between  $U(t)$  and local decisions

Fig. 4 demonstrates the relationship between  $U(t)$  and local decisions. It provides a schematic view of how  $U$  is aggregated with time  $t$  through the proposed fuzzy-set-based theoretical reasoning, with the above specified simplifications. As can be seen, when the sensors involved are endowed with equal rights, the final decision will be high when more than half of the local decisions are high, and will be low otherwise.

Fig. 5 illustrates the screen output of the belief generation experiment based on the Berkeley notes. Each line represents the receipt of a component of a partial decision message. The decision threshold is set to 0380h. In the case of decision level belief-generation (Fig. 5(a)), the partial decisions (11 11h for H1, 00 00h for H0) from sensors are then fused into a decision matrix, the output of which is a dynamic decision on the spot. Partial decisions are normalized to 0.125 maximum.

The partial decision H0 stands for normal situation, while H1 stands for abnormal situation. In the case of raw data level belief-generation, raw data are fused and the local decisions are made at the BS, as shown in Fig. 5(b). However, as will be analyzed within the following section, raw-data-level belief generation consumes more energy than decision-level belief generation.



incorrect message. In fact, the problem of message loss deserves more consideration than false alarm rate because of the multi-hop nature of WSNs. For a decision  $d_j$ , suppose the failure rate for each hop  $i$  is  $P_{fci}$ , then the probability of successful routing of the  $j^{\text{th}}$  message,  $P_{cj}$ , is decided by:

$$P_{cj} = \prod_{i=1}^M (1 - P_{fci}) \quad (27)$$

where  $M$  is the number of hops. If all  $p_{cfi}$  of neighbouring WSN nodes are treated as equal, or

$$p_{cfi} = p_{cfk}, \forall i, k \in [1, M]$$

, then the relationship of routing success rate and hopping failure rate is demonstrated in Fig. 6. It can be seen that the routing success rate decreases in an exponential manner as  $p_{cfi}$  increases. Therefore, there will be serious problems if hopping failure rates are considerably high. This result suggests that lessening the number of hops could substantially improve the quality of communication and make the belief generation process more robust.

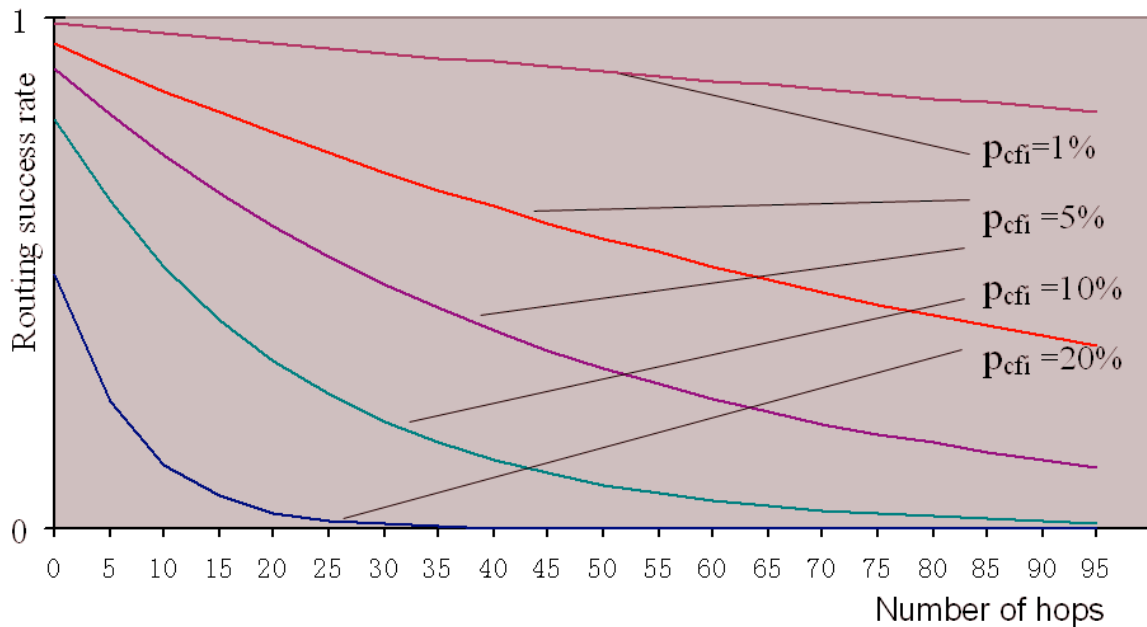


Fig. 6 Routing success rate decreases as the number of hops increases

### 5.3.2 Time Cost for Belief Generation

Time cost is crucial to a monitoring system whose primary task is to monitor the physical or chemical dynamics of a designated area and make decisions as quickly as possible. Decisions, whether made locally or centrally, are made based on local data. The difference is that, for raw data level belief-generation, the raw data needs to be routed back to the BS before a local decision is made; while for belief generation at the decision level, the local decisions are made locally and then routed back to the BS for fusion. In other words, the cost differences are mainly caused by communication time. Thus, it is necessary to compare the communication time costs of the fusion on differing levels. Without losing generality, we assume that each local decision is made based on an average of 270 bytes of raw data (including format bytes), and the smallest message packet is 30 bytes in length.

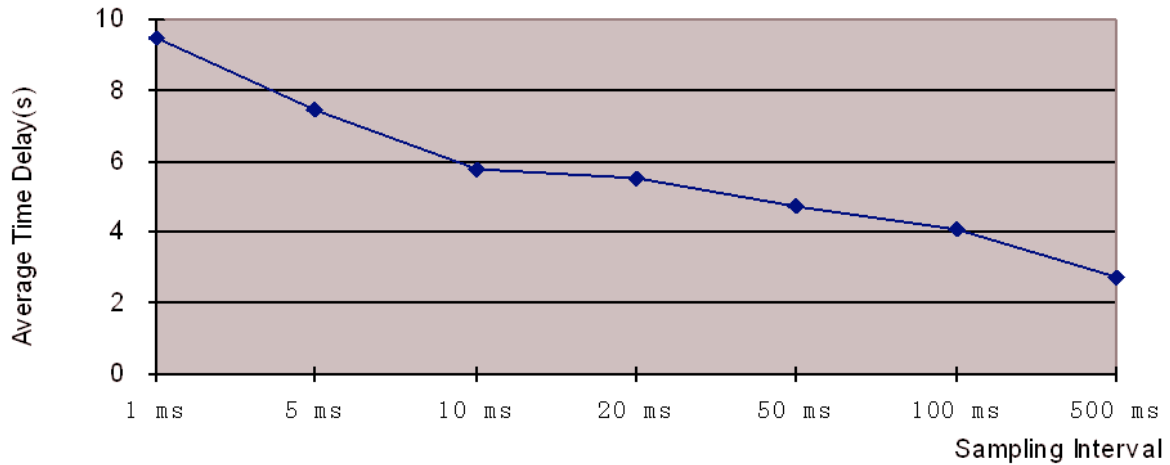


Fig. 7 Relationship between average time delay and sampling interval

For raw level belief generation, the 270 bytes data needs to be sent through multi-hop routing to the BS, therefore the communication workload is 270 bytes. For belief generation at the decision level, on the other hand, a local decision is small enough to be packed into a single piece of message; therefore the communication workload is 30 bytes.

For belief generation at the feature level, the communication workload is somewhere between 30 bytes and 270 bytes. We suppose that the communication workload for feature level is 90 bytes (including format bytes). Consequently, the communication workloads of belief generation on each level - raw data, feature and decision, approximately result in a 9:3:1 ratio.

Communication workload is pivotal to the time needed for the messages to arrive at the BS. More specifically, with a contention-based communication mode when the workload is heavy, some messages are delayed, while others might not be received. Suppose that for  $i^{\text{th}}$  round test, it takes  $T_{li}$  and  $T_{hi}$  for a message to arrive at the BS in a vacant channel and a busy channel respectively,

$$\frac{\sum_{i=1}^M (T_{hi} - T_{li})}{M}$$

then the average time delay derived from  $M$  round tests is

Fig. 7 demonstrates an experiment on average time delay by collecting randomly designated messages from eight neighbouring sensors to the BS at certain sampling intervals. The X-axis is the sampling interval which can be considered as data volume, while Y-axis represents average time delay. The results show that the larger the data volume within the interested communication channel, the longer the delay time, and therefore the higher the potential for error when delivering messages. The main reason for this is that some nodes fail when contenting for channels and fail to route their messages to the next node.

### 5.3.3 Energy Cost for Belief Generation

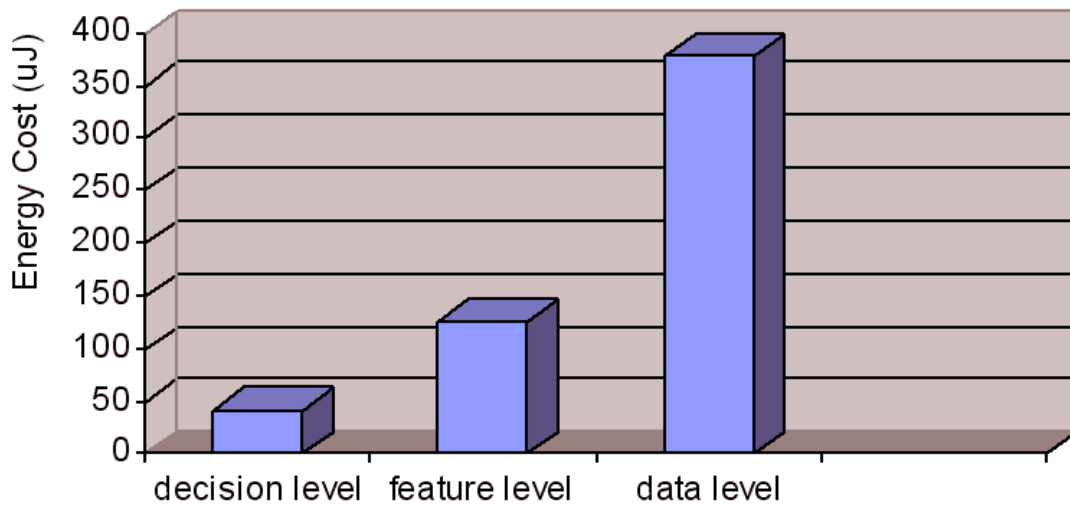


Fig. 8 Energy cost of belief generation on decision, feature and data level

The largest energy expense of a WSN node is that of communication (Hill 2003). For simplicity, we omit the energy cost of local analysis and decision-making due to their relatively minor contribution to the entire energy expenditure. To analyse and compare energy costs of belief generation on different levels, the simple assumption described in (Rabiner et al. 2000) is adopted. Recall that to transmit an  $m$ -bit message to distance  $d$  expends  $m \cdot (50 + 0.1 \cdot d^2)$  (nJ) and to receive this message, the radio expends  $50 \cdot m$  (nJ). If a message is sent through  $H$  hops and finally reaches the BS, then the hopping energy expense  $E_H$  is roughly expressed as  $E_H = m \cdot (100 + 0.1 \cdot d^2)$  (nJ).

The entire energy consumption for wireless communication is proportional to message length. Fig. 8 demonstrates the comparison on energy consumption of a single message routing on data, feature and decision levels, supposing that the event message is ten hops away from the BS. With the same assumptions adopted in the previous section, the communication energy costs of belief generation on raw data level, feature level and decision level display a 9:3:1 ratio. This indicates that belief generation at the decision level is the most energy efficient.

### 5.3.4 Discussion

Energy consumption and the communication time cost of belief generation demonstrates a direct relationship to message length, and therefore raw level belief generation generates the greatest overhead, while decision-level belief generation generates the lowest. This suggests that belief generation at the decision level is the best strategy. Therefore, the more distributed the processing and the reasoning, the lower the fusion overhead, and the faster the fusion occurred. Such distributed characteristics will become increasingly important for next-generation WSN applications as processing and storage abilities of sensor hardware improve. As WSNs grow in size and sophistication, the need for an intelligent capacity will become more urgent if autonomic behaviours are to be realised.

## 6 Conclusion

A prerequisite to the successful deployment of agents within WSNs is a capability to reason in a distributed manner and with partial, noisy and incomplete knowledge. In the case of BDI agents, this has implications for the belief generation process. In this paper, local decision-making and

fuzzy-set-based theoretical reasoning are combined in order to deliver energy-aware and utility-based agents capable of supporting belief generation within the constrained environments of wireless sensor networks.

This paper has described the design and operation of energy-aware and utility-based agents. It has focused in particular upon the core issue of belief generation within computationally challenged environments. It has outlined experimental work and initial results that support the efficacy of the proposed approach. Energy-aware utility-based agents offer a hybrid approach to deliberative reasoning by combining fuzzy reasoning with classical BDI approaches.

### Acknowledgements

The authors would like to thank the reviewers for their insightful comments and observations. Gregory O'Hare and Michael O'Grady gratefully acknowledge the support of Science Foundation Ireland (SFI) under Grant No. 03/IN.3/1361.

### References

- Alechina N, Logan B (2002) Ascribing beliefs to resource bounded agents. In: Proceedings of the First international Joint Conference on Autonomous Agents and Multiagent Systems: Part 2, 881-888
- Bratman ME (1987) Intentions, Plans, and Practical Reason. Harvard University Press: Cambridge, MA.
- Breese JS, Fehling MR (1990) Control of problem-solving: Principles and architecture, In: Proceedings of the Fourth Annual Conference on Uncertainty in Artificial intelligence, 59-68.
- Boella G, Hulstijn J, Van der Torre L (2005) Decision-Theoretic Deliberation in Resource Bounded Self-Aware Agents. In: Proceedings of the 7th International Symposium on Logical Formalizations of Commonsense Reasoning (CommonSense05).
- Boutilier C (1994) Towards a logic for qualitative decision theory, In Proceedings of the Fourth International Conference on Knowledge Representation and Reasoning, 75-86
- Chamberland, J., Veeravalli, V. V. (2003) Decentralized Detection, in Sensor Networks. IEEE Trans. Signal Processing, 51:407-416.
- Chen H, Mineno H, Mizuno T (2006) A Meta-Data-Based Data Aggregation Scheme in Clustering Wireless Sensor Networks. In: Proceedings of the 7th International Conference on Mobile Data Management, 43-49
- Cohen PR, Levesque HJ (1990) Intention is choice with commitment. Artif. Intell. 42(2-3):213-261.
- Corchado JM, Laza R (2002) Construction of BDI Agents from CBR systems. In: Proceedings of the 1st German Workshop on Experience Management, 47-60
- Dasarathy B (1994) Decision Fusion. IEEE Computer Society, New York
- Dastani M, Hulstijn J, Van der Torre L (2000) BDI and QDT: a comparison based on classical decision theory. In: Proceedings of AAAI Spring Symposium GTDT01, 16-26
- Fok CL, Roman GC, Lu C (2005) Mobile Agent Middleware for Sensor Networks: An Application Case Study In: Proceedings of the 4th International Conference on Information Processing in Sensor Networks (IPSN05), 382-387
- Goldman CV, Allen M, Zilberstein S (2007) Learning to Communicate in a Decentralized Environment, Autonomous Agents and Multi-Agent Systems 15(1):47-90
- Hill J (2003) System Architecture for Wireless Sensor Networks. PhD Thesis, University of California, Berkeley
- Ho Ngoc D (2003) Representing Knowledge of Resource-bounded Agents. In: Proceedings of the Fourth ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD03), 466-471
- Hu J, Blum R (2001) On the optimality of finite-level quantization, for distributed signal detection. IEEE Trans. Information Theory, 47:1665-1671.
- Kalpakis K, Dasgupta K, Namjoshi P (2003) Maximum Lifetime Data Gathering and Aggregation in Wireless Sensor Networks. Computer Networks 42:697-716
- Keegan S, O'Hare GMP, O'Grady MJ (2008) Easishop: Ambient intelligence assists everyday shopping. Information Sciences, 178(3):588-611
- Koch F, Meyer J-J, Dignum F, Rahwan I (2005) Programming Deliberative Agents for Mobile Services: the 3APL-M Platform. In: Proceedings of the Workshop on Programming Multi-Agent Systems (ProMAS05). LNAI 3862:222-235

Kumar M, Schwiebert L, Brockmeyer M (2004), Efficient Data Aggregation Middleware for Wireless Sensor Networks, WSU-CSC-NEWS/04-TR02. Wayne State University, Available via [http://newslab.cs.wayne.edu/technical\\_reports.htm](http://newslab.cs.wayne.edu/technical_reports.htm) Accessed May 2008

Luo X, Jennings NR, Shadbolt N, Leung H, Lee JH (2003) A fuzzy constraint based model for bilateral, multi-issue negotiations in semi-competitive environments. *Artificial Intelligence* 148 (1-2):53-102

Muldoon C, O'Hare GMP, Collier RW, O'Grady MJ (2006) Agent Factory Micro Edition: A Framework for Ambient Applications. In: *Proceedings of the International Conference on Computational Science (ICCS2006)*. LNCS 3993:727-734

Niu R, Varshney PK (2005) Decision Fusion in a Wireless Sensor Network with a Random Number of Sensors. In: *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing*, 861-864

Niu R, Varshney PK, Moore M, Klamer D (2004) Decision fusion rules in multi-hop wireless sensor networks. In: *Proceedings of the 7th International Conference on Information Fusion*, 21-27

O'Grady MJ, O'Hare GMP, Donaghy C (2007) Delivering Adaptivity through Context Awareness. *Journal of Network and Computer Applications* 30(3):1007-1033

O'Hare GMP, Jennings, NR (1996) *Foundations of Distributed Artificial Intelligence*. Wiley, New York

Olivia C, Chang CF, Enguix CF, Ghose AK (1999) Case-Based BDI Agents: An Effective Approach for Intelligent Search on the World Wide Web. *AAAI Spring Symposium on Intelligent Agents*, 1-8

Pearl J (1993) From conditional ought to qualitative decision theory. In: *Proceedings of the Ninth Conference on Uncertainty in Artificial Intelligence*, 12-20

Przydatek B, Song D, Perrig A (2003) SIA: secure information aggregation in sensor networks. *Proceedings of the First International Conference on Embedded Networked Sensor Systems*, 255-265

Qi H, Kuruganti PT, Xu Y (2002) The Development of Localized Algorithm in Wireless Sensor Networks. *Sensors* 2:286-293.

Rabiner W, Heinzelman CA, Balakrishnan H (2000) Energy-Efficient Communication Protocol for Wireless Micro-sensor Networks. In: *Proceedings of the 33rd International Conference on System Sciences (HICSS 00)*, 3005-3014

Rao AS, Georgeff MP (1992) An Abstract Architecture for Rational Agents. In: *Proceedings of Knowledge Representation and Reasoning*, 439-449

Rao AS, Georgeff MP (1995) BDI Agents: From Theory to Practice. In: *Proceedings of the First International Conference on Multi-Agent Systems*, 312-319

Ruzzelli A, O'Hare GMP, O'Grady MJ, Tynan R (2005) Adaptive Scheduling in Wireless Sensor Networks. In: *Proceedings of 2nd IFIP International Workshop on Autonomic Communication*, LNCS 3854:266-276

Schut M, Wooldridge M (2001) The Control of Reasoning in Resource-Bounded Agents. *Knowledge Engineering Review* 16(3):215-240.

Shen S, O'Hare GMP, Diamond D, Marsh D, Ruzzelli A (2006) ATOM: Atomic Topology Management of Wireless Sensor Networks. In: *Proceedings of IFIP Autonomic Networking Conference*, LNCS 4195:243-254

Shen S, O'Hare, GMP (2007). Wireless Sensor Networks, an Energy-Aware and Utility-Based BDI Agent Approach. *Int. J. Sensor Networks* 2(3-4):235-245

Singh MP, Asher NM (1991) Towards a formal theory of intentions. In: *Logics in AI -Proceedings of the European Workshop*, LNAI 478:472-486

Vasilakos A, Pedrycz W (2006) *Ambient Intelligence, Wireless Networking, Ubiquitous Computing*. Artec House, Norwood

Wooldridge M (2000) *Reasoning about Rational Agents*. The MIT Press, Cambridge, MA

Wooldridge M, Jennings N (1995) Intelligent Agents: Theory and Practice. *Knowledge Engineering Review*. 10(2):115-152

Yu CT, Varshney PK (1998) Paradigm for Distributed Detection Under Communication Constraints. *Optical Engineering*, 37:417-426.

Zadeh LA (1965) Fuzzy sets. *Information and Control* 8(3):338-353.

Zilberstein S, Russell SJ (1996) Optimal composition of real time systems. *Artificial Intelligence* 82(1-2):181-213

Younis O, Krunz M, Ramasubramanian S (2006) Node clustering in wireless sensor networks: recent developments and deployment challenges. *IEEE Network*, 20(3):20-25