

An Intelligent Sensor Network for Oceanographic Data Acquisition.

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Abstract. In this paper we describe the deployment of an offshore wireless sensor network and the lightweight intelligence that was integrated into the data acquisition and forwarding software. Although the conditions were harsh and the hardware readily available, the deployment managed to characterise an extended period due to some unique algorithms. In-situ adaptation to differences in data types, hardware condition and user requirements are demonstrated and analysis of performance carried out. Statistical tests, local feedback and global genetic style material exchange ensure limited resources such as battery and bandwidth are used efficiently by manipulating data at the source.

1 Introduction

Research into wireless sensor networks is not new [1,2,3] and networks of devices are already being deployed [4], but robust and efficient deployment of these networks will require hands-off configuration and management as the size of these networks increases.

Efficient and effective parameter measurement of oceanographic environments is an ongoing challenge in itself but also serves as a useful test case for applying sensor networks and assessing the performance of on-board intelligence. For dynamic, real world scenarios it is preferable for devices to make decisions in real time that adapts to limiting parameters (battery life, network conditions etc) and conditions (temperature, wave height etc). Enabling a device to make good decisions in real time is one type of artificial intelligence. This paper proposes a hybrid algorithm that is shown to fulfil some of the important requirements.

Monitoring of environmental conditions also serves as a useful test case for more heterogeneous pervasive networks [5]. Mobile phones, laptops, PDAs all have limited network, hardware and battery power but extensive functional capabilities, getting the most out of these devices in an increasingly networked society is a primary goal for ICT research.

2 EXPERIMENTAL DESIGN

The remit of this project was to replace single expensive monitoring stations with cheaper, connected devices that operated as an intelligent network. There is some evidence that many less accurate devices can characterise an area better than a single accurate device.

2.1 SECOAS

The Self-Organising Collegiate Sensor (SECOAS) Network Project [3,7] is a collaborative effort that is providing original solutions to implementation of offshore wireless sensor networks [8]. Simple, 'off-the-shelf' hardware has been used that works together to characterise the conditions of an area of coastline, the test site is an off-shore wind farm [9] where the impact of the structure is largely unknown. This is made possible by a range of onboard AI that simultaneously aims to conserve battery power, optimise bandwidth usage, compress data and assess the usefulness of data. Most types of behaviour can be pre-programmed, a device can be told in advance what to sense, when to forward, when to compress etc but this type of pre-programmed behaviour relies on accurate knowledge of the system being studied, the hardware used and the conditions of the trial. This knowledge is seldom accurately known which leads to inefficient use of resources. This could be expressed as oversampling of relatively uninteresting periods and undersampling of interesting periods or, completing the experiment with unused battery power or the sampling period being cut short to overuse of the battery. A truly adaptive approach could make best use of resources and reconfigure even when catastrophic events such as the loss of a node occurs

Like all wireless sensor network systems, resources such as battery power will be limited in the SECOAS project [10,11]. Analogue to digital converters, microchips and radio equipment all use battery power, so the usefulness of every reading needs to be assessed on the node, to save resource expensive transmission.

6 buoys were deployed for 2 weeks in October 2004. One of which is shown in figure 1. The buoy was anchored in position and had also had a tethered sensing module (figure 1). And RS232 interface was used between the network module and the sensing module with the purpose of collect sampling data.

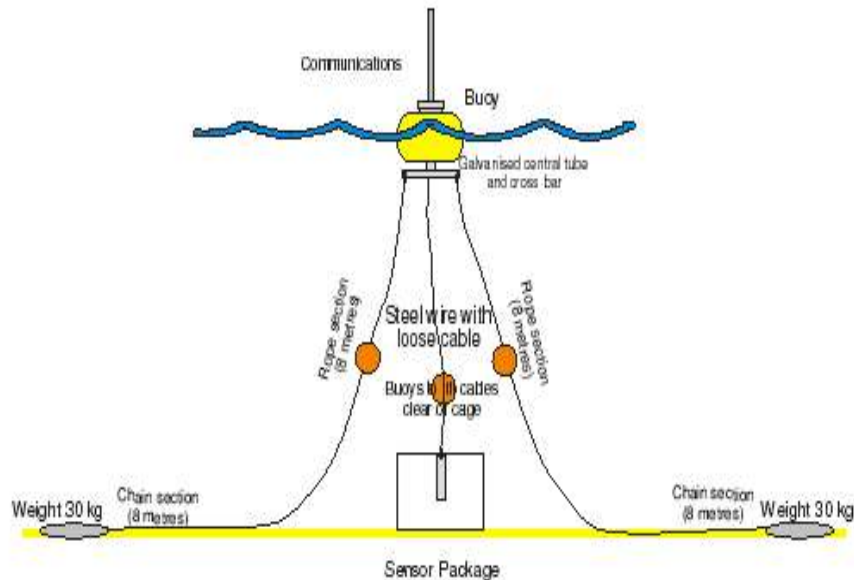


Fig. 1. Schematic of deployed buoy and attachments.

2.2 ARNEO (Autonomous Resilient Network for Environmental Observation)

Wireless propagation can be seriously affected during periods when exceptional events of interest might be happening (e.g. storms or intense wave activity), and since they can last for long periods and are very difficult to predict, activity-aware mechanisms for data communication which avoid energy starvation are required. The opportunities for transmissions are scarce and shorter in range; additionally expected error rate is high. Devices can be temporarily or permanently obstructed from performing due to a multitude of reasons that cannot be reasonably avoided. The causes are extremely varied, thus aiming to predict or manage individual cases would make decision taking inefficient. The system must dynamically self-reconfigure functional communication paths as needed. Multi-hop communication is required for covering vaster areas than can not be covered using other wireless configurations, in addition of providing resilience to individual failure.

Deployments must adaptively handle situations ranging from small to large numbers of heterogeneous devices, from sporadic small areas of intermittent obstructions to complete communication blackouts lasting many hours, from operating with the entire device population to a large proportion temporally buried, blocked or damaged. Whereas disruptive factors cannot be eradicated, it is possible to reduce the negative impact they produce on message recovery.

Autonomous Resilient Network for Environmental Observation Systems (ARNEO) provides network services for interconnecting sensors and consequently providing access to scientific models in line with the requirements of Environmental observation. ARNEO is an autonomous wireless ad hoc sensor network providing resilient transport across dense sensor deployments and scientific models of environmental phenomena.

It is expected that the collection of data produced at large by the sensor population possess strong correlation and redundancy. It is clear that isolated samplings may provide little information towards the understanding of the phenomena in comparison to the information provided by the majority of the deployment. Nevertheless, it also indicates that collecting a high percentage of generated samplings can still produce sensible depiction of the phenomena depending of the scientific model. Under certain considerations, scientific models may evaluate the possibility of having their demands satisfied with lower recover rates.

Our longer term intention for ARNEO is to create a large scale multi-hop network; however, during the described trial it was decided to experiment with a simple single cluster of six nodes as a representative of the target system. Wireless devices based on a microcontroller of the series PIC 16XXX and radio modules at 173.25 MHz were deployed using a STDMA hierarchy as in [12]. Tools, instruments and programs were deployed to record relevant parameters and collection of sampling data and synchronisation parameters

2.3 Hybrid Data Handling Algorithm

In the context of a sensor network data handling can be seen as anything involved with the acquisition, mathematical manipulation and forwarding on of environmental measurements. The 'algorithm' we use for this involves the data passing through several rounds on analysis and manipulation, versions of which have been used for other ad-hoc and active network tasks [13,14]. Firstly, before the readings are even stored on the data logger some preprocessing occurs but this occurs on the monitoring device so can be ignored. The major decisions are what to do with the data on the logger. Given enough bandwidth and enough battery every single reading would be sent back to the base station but this is not feasible.

The first decision involves passing the data through a 3 entry sliding window looking for sufficient deletion conditions. Given a time-series of sensor readings at t_0 , t_1 , t_2 a simple analysis of the reading at t_1 can decide how useful it is. If the reading at t_1 is the average of the readings at t_0 and t_2 then its deletion will make no effect on the characterisation of a time series, given that it's value can be interpolated from readings at t_0 and t_2 . A deviation from the average by a small amount may also be acceptable if improved compression is required. A trade off between loss of information and compression must be made.

Next we use internal condition monitoring that affects the frequency of some actions, using negative feedback to obtain a homeostatic behaviour. A node may carry out none, one or many actions during a specific time period. Actions such as sensing, forwarding and queue management. Each action has a cost in terms of queue occupancy, battery usage and bandwidth usage. By monitoring the condition of these resources the probability of carrying out these actions can be modified. For instance, if the queue length is near it's maximum it would be prudent to take fewer readings and/or to do more forwarding or if the battery is being used at an unsustainable rate higher battery usage behaviours should be reduced and lower usage ones increased. We term this 'local learning'.

Finally, a genetic style transfer and fitness based evaluation of internal performance parameters can enable nodes that are performing well to share their configuration with nodes that are performing less well. Methods 1 and 2 both involve several parameters, values that effect the performance (e.g. Reading at T1 is deleted if + or - Z% of the average of Reading T0,T2. Sensing probability is reduced by X if queue is above Y). Effective values for these parameters are discovered in advance using multi-parameter optimisation on a simulated environment. But this can only be as good as the simulated environment. By encoding these parameters in a genetic fashion the performance of the nodes can be evaluated and the genetic material for the 'fittest' nodes can be spread, while the genetic make up of the less fit nodes is modified or dies out.

3 Results

While 6 nodes were deployed (see figure 2 for example) only 2 gathered data for the whole 2 week period, 2 more gathered data for part of the period. Data for electrical conductance, temperature, pressure (from which wave height can be inferred) and turbidity were collected on the data logger and minutely intervals [figures 3-6 show data over various time ranges]

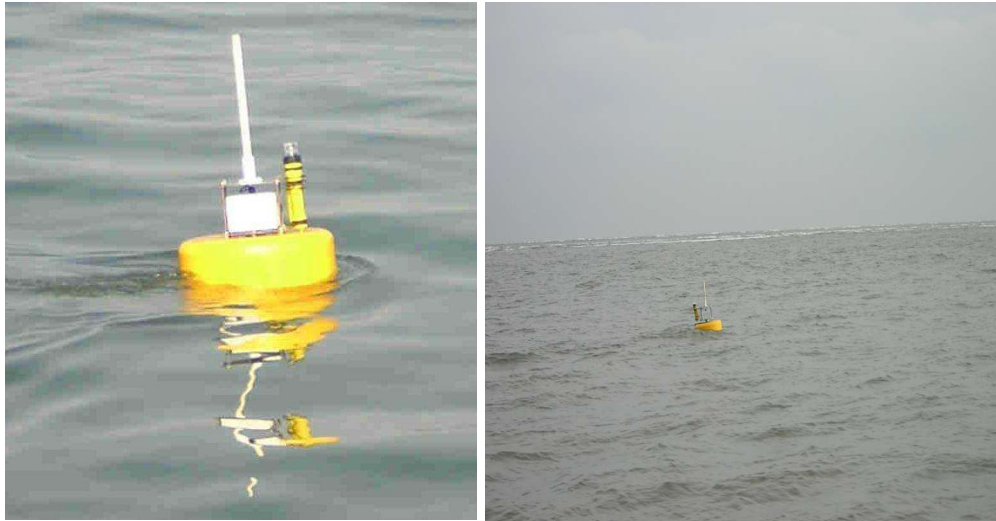


Fig. 2. Deployed Buoys off Scroby Sands

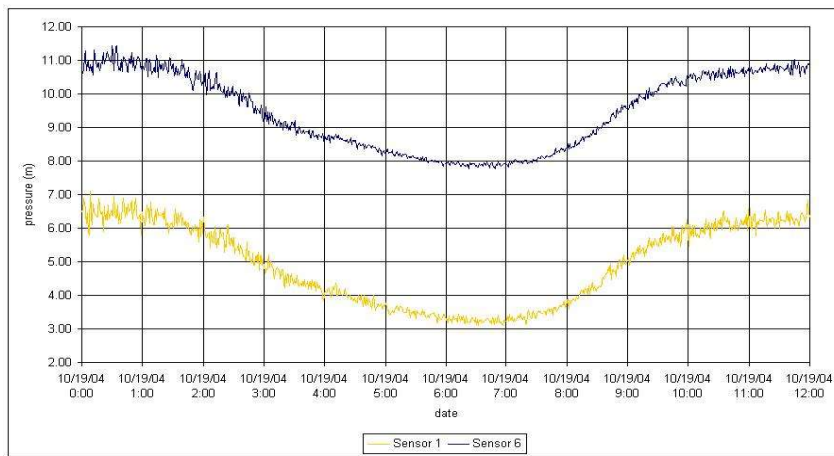


Fig. 3. Readings depth (derived from pressure) at 2 buoys over 12 hours

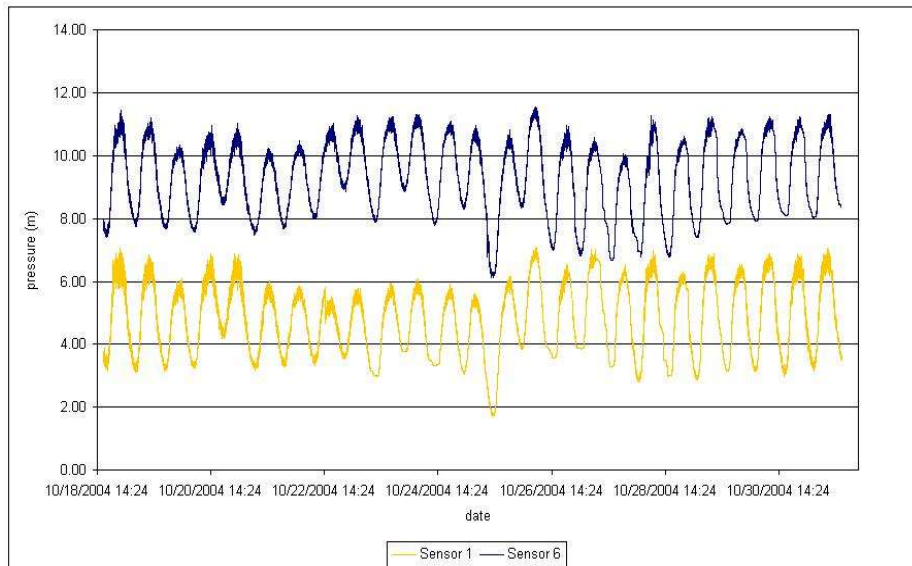


Fig. 4. Readings for depth (derived from pressure) at 2 different buoys over 3 weeks

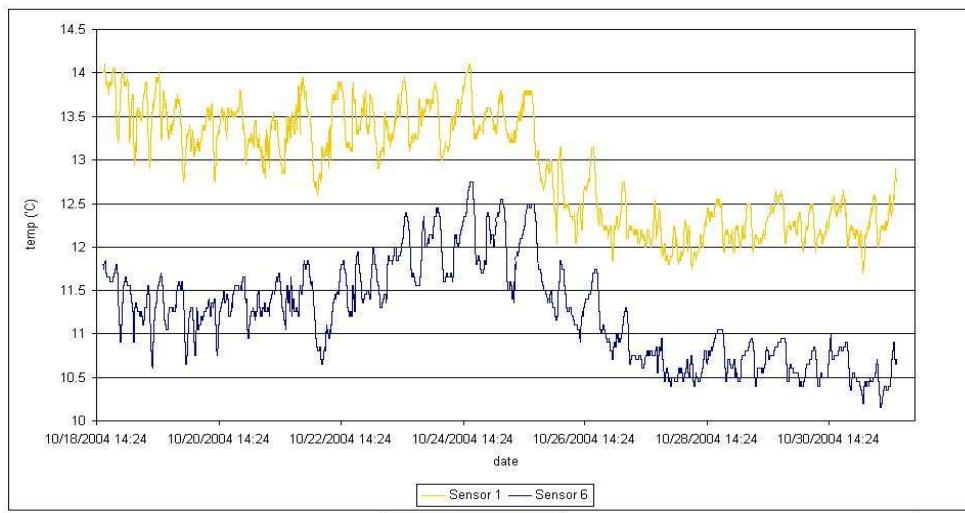


Fig. 5. Readings for temperature from 2 different buoys over 3 weeks

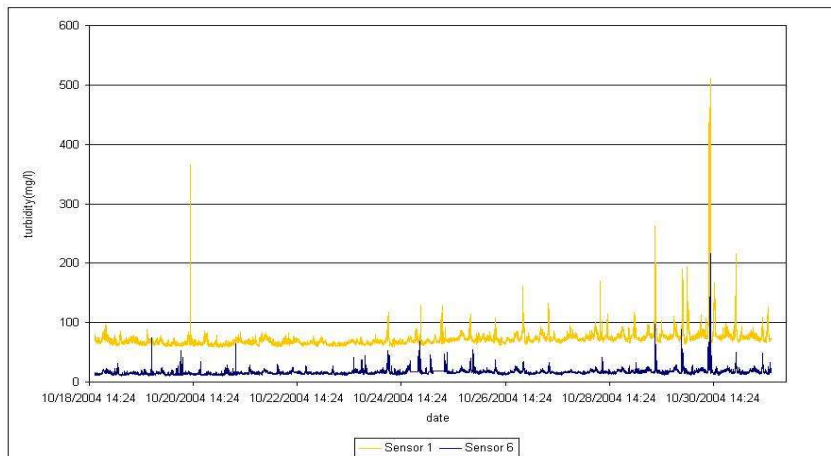


Fig. 6. Readings for turbidity from 2 different buoys over 3 weeks

More details on the deployment specifics are presented elsewhere [8,15] as are details of the radio based data transmission [12]. For the purposes of this paper we were interested in how the data gathered was handled and how this compared to other methods that could have been applied. Firstly, if we look at the data logged at 2 nodes we will see that the profile differs for each reading type (figs 3-6) and differs from node to nodes (fig 3-6). For example temperature varies less wildly and than turbidity, pressure has a strong periodic behaviours (tidal), temperature is different at different nodes. There are other less obvious characteristics in the dataset. Any real time data handling software must be able to adapt to different data profiles in real time regardless of how many underlying trends and characteristics are

This variation in behaviour has an effect on optimal compression. Table 1 shows how different methods of compression and forwarding (sliding window, round robin etc) perform on different datasets (pressure, temperature, turbidity). The variables were tuned so that all compression techniques over all sensor datasets compressed the data by 50% with the exception of ‘sliding window’ for turbidity and pressure. This is because the sliding window approach requires the middle value of three to vary by less than X% before it can be deleted, both turbidity and pressure we too variable for a sensible value for X to be found.

It is apparent that for less volatile datasets (temperature) a simple, non-adaptive approach like round robin sampling performs well but for more complex, volatile datasets a more adaptive approach performs better. Over the long term evolvable parameters should produce a more stable and robust solution but due to the inevitable introduction of mutated variables performance over the short term may be inferior.

Evolvable parameters appear to improve performance for turbidity and temperature but incur an overall cost for pressure readings, possible due to their volatile nature.

While at this stage different algorithms seem to be optimal, the aim is to modify the algorithm so that it can adapt to be optimal in all situations. This will be explored in experiments later in 2005

Table 1. Performance of different algorithms at in-situ data compression (*less than 50% compression achieved)

	Absolute error (bits)		
	Sensor (average)		
	turbidity	pressure	temperature
Random sampling	7837	12005	543
Round robin sampling	6277	8573	274
Sliding Window (SW)	4236*	15015*	221
SW + local learning (LL)	4491	7120	645
SW + LL + evolvable parameters	4340	7559	347

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