AN ALGORITHM FOR GREEN COMMUNICATION SIGNAL RECONSTRUCTION IN WIRELESS SENSOR NETWORK.

CASE STUDY KENYA PRISONS TELECOMMUNICATION

By

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DECLARATION

I declare that this Dissertation is my original work and has not been previously published or submitted elsewhere for award of a degree. I also declare that this contain no material written or published by other people except where due reference is made and author duly acknowledged

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I do hereby confirm that I have examined the Masters Dissertation of

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And have approved it for examination

Sign: ………………… Date. ………………….

……………………………….
Dissertation Supervisor

DEDICATION

I dedicate this masters dissertation to my lovely wife Mary Makena and my son who sis seven years old Joshua Mumo and Hope Ushindi my three year old daughter for hope and determination they inspired either directly or indirectly without forgetting my supervisors Dr. Alice Njuguna and co-supervisor Mr. Matende for support they offered during the writing of this research document

I also find it joyful and honor to appreciate and acknowledge those who also participated indirectly by either giving their advice, financial support and ideas and any other support which contributed to the success of this study. Those among others include Mr. Etiko of communication authority of Kenya (CAK), Dr. Gilbert B. Mugeni, Ph. D of CAK, Dr. Mwendia, Dr. Aboke of Technical University of Kenya (TUK) and the commissioner General of prisons beside many other who could not be mentioned for unwavering support, May the almighty God bless you all

LIST OF ABBREVIATIONS

Abbreviation	Description
WSN	Wireless sensor Network
FC	Fusion Center
PF	Particle filtering
Pdfs	Probability density function
MSE	mean square error
KF	Kalman Filters
SNR	Signal-to-noise ratio
EKF	extended Kalman filters
CKF	cubature Kalman Filter
PM	pseudo-measurement
SLRKF	Statistical linear regression Kalman filters
UKF	Unscented Kalman filter
CS	Compresses Sensing
DKF	Distributed Kalman Filters
BEP	Bit error probability
RMS	Root mean square
CAPEX	Capital expenditure
CPU	Central processing unit
DSN	Distributed sensor Network
IoT	Internet of things
5G	5 Generation
CSKF	Centralized Cubature Kalman Filter
CIF-PM embedded	Cubature Information Filters with Pseudo-Measurement
SCIF-PM	Stable Cubature Information Filter with Pseudo-measurement

SRCIF-PM	Square-Root cubature Information Filtering with Pseudo Measurement Embedded
DSRCIF-PM	Distributed square-root cubature information filtering with Pseudo-Measurement Embedded
D2D	Device to Device Communication
OPEX	Operational expenditure
LMS	least mean square
RF	radio frequency
IF	intermediate frequency
CDS	Connected Dominating sets (CDS)
EECDS	Energy Efficiency CDS

LIST OF SYMBOLS

Symbol	Definition
$P(\cdot)$	Probability density function.
$\mu_{x\rightarrow f}$	Message from a variable node to a function node
$\mu_{f\rightarrow x}$	Message from a function node to a variable node
$\mathcal{N}$	Number of particle in morte-Carlo integration
$D(R)$	Distortion rate
L	Number of quantization levels.
σ_X^2	MSE
I_F	Fisher information
π	Bit sensor assignment
$\ell(\cdot)$	Feasible labeling for the vertices of the graph
G_ℓ	Equality graph according to labeling ℓ
ν	Number of inputs messages to a function node in FG
S_k	Number of sensor tracking the target at time *k*
Y	Noisy measurement
W	Measurement noise
Z	Quantized measurement
T	Received symbol at channel output
n	Total number of nodes in WSN topology
k	Number of clusters in WSN topology
k_{opt}	Optimum number of clusters in WSN topology
$\frac{n}{k}$	Average number of clusters in WSN topology
α	Path loss constant
D_{TR}	Distance between transmitter and receiver
G	Eligibility constant for cluster head selection
$E_{Cluster}$	Energy dissipated in a cluster

$[N]$	The set of the natural numbers not exceeding N, i.e,$\{1,2, \dots \dots \dots . N\}$
S	Usually a subset of $[N]$
ℓ_p^N	The space $\mathbb{C}^N$ equipped with the ℓ_p- (quasi) norm.
$\|X\|_p$	The ℓ_p- (quasi) norm of a vector **x**
δ_s	The sth restricted isometry constant of a matrix.
μ_1	The ℓ_p- Coherence function of a matrix
η	Usually an upper bound on the measurement error, i.e.$\|e\|_2 \leq \eta$
ε	Usually a small probability

ABSTRACT

Environmental consideration provides news trends in wireless communication network known as green communication. The main object of green communication is to save as much as possible the energy consumption of the communication system. In this research study, We have investigated the green distributed nonlinear state estimation problem in wireless sensor networks (WSNs).which will be seamlessly integrated with the forthcoming 5G communication system's distributed signal reconstruction algorithm is developed by employing compressive sensing and consensus filter to solve sparse signal reconstruction issue in WSNs with energy efficiate considered. In particular, the pseudo-measurement (PM) technology is introduced into the Kalman filter(CKF),and a sparsity constraint is imposed on the nonlinear estimation CKF.inorder to develop a distributed reconstruction algorithm to fuse the random linear measurement from the nodes in WSNs,the PM embedded CKF is formulated into the information form, and then the derived information filter is combined with consensus filter, while the square-root version is further developed to improve the performance and strengthen power saving capability. The simulation result demonstrate that the signal can be reconstructed with much fewer nodes in decentralized manner and all the nodes can reach a consensus, while providing some attractive benefits to the green 5G communication system

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CHAPTER ONE

INTRODUCTION

This chapter provides a first introduction to the WSNs, including architecture, specific characteristics and applications.

1.0 BACKGROUND OF THE STUDY

1.0.1. Wireless sensor Network

The well-known IEEE 802.11 family of standards was introduced in 1997 and is the most common wireless networking technology for mobile systems. It uses different frequency bands, for example, the 2.4-GHz band is used by IEEE 802.11b and IEEE 802.11g, while the IEEE 802.11a protocol uses the 5-GHz frequency band. IEEE 802.11 was frequently used in early wireless sensor networks and can still be found in current networks when bandwidth demands are high (e.g., for multimedia sensors). However, the high-energy overhead of IEEE 802.11 based networks makes this standard unsuitable for low-power sensor networks. Typical data rate requirements in sensor networks are comparable to the bandwidths provided by dial-up modems, therefore the data rates provided by IEEE 802.11 are typically much higher than needed. This has led to the development of a variety of protocols that better satisfy the networks' need for low power consumption and low data rates. For example, the IEEE 802.15.4 protocol has been designed specifically for short range communications in low-power sensor networks and is supported by most academic and commercial sensor nodes. When the transmission ranges of the radios of all sensor nodes are large enough and the sensors can transmit their data directly to the base station, they can form a star topology. In this topology, each sensor node communicates directly with the base station using a single hop. However, sensor networks often cover large geographic areas and radio transmission power should be kept at a minimum in order to conserve energy; consequently, *multi-hop communication* is the more common case for sensor networks. In this *mesh topology*, sensor nodes must not only capture and disseminate their own data, but also serve as *relays* for other sensor nodes, that is, they must collaborate to propagate sensor data towards the base station. This *routing* problem, that is, the task of finding a multi-hop path from a sensor node to the base station, is one of the most important challenges and has received immense attention from the research community. When a node serves as a relay for multiple routes, it often has the opportunity to analyze and pre-process sensor data in the network, which can lead to the elimination of redundant information or aggregation of data that may be smaller than the original data.

1.0.1. History of wireless sensor networks

The military has been a driving force behind the development of wireless sensor networks. For example, in 1978, the Defense Advanced Research Projects Agency (DARPA) organized the Distributed Sensor Nets Workshop (DAR 1978), focusing on sensor network research challenges such as networking technologies, signal processing techniques, and distributed algorithms. DARPA also operated the Distributed Sensor Networks (DSN) program in the early 1980s, which was then followed by the Sensor Information Technology (SensIT) program.

In collaboration with the Rockwell Science Center, the University of California at Los Angeles proposed the concept of Wireless Integrated Network Sensors or WINS. One outcome of the WINS project was the Low Power Wireless Integrated Micro sensor (LWIM), produced in 1996. This smart system was based on a CMOS chip, integrating multiple sensors, interface circuits, digital signal processing circuits, wireless radio, and microcontroller onto a single chip. The Smart Dust project at the University of California at Berkeley focused on the design of extremely small sensor nodes called *motes*. The goal of this project was to demonstrate that a complete sensor system can be integrated into tiny devices, possibly the size of a grain of sand or even a dust particle. The Pico Radio project by the Berkeley Wireless Research Center (BWRC) focuses on the development of low-power sensor devices, whose power consumption is so small that they can power themselves from energy sources of the operating environment, such as solar or vibrational energy. The MIT μAMPS (micro- Adaptive Multidomain Power-aware Sensors) project also focuses on low-power hardware and software components for sensor nodes, including the use of microcontrollers capable of dynamic voltage scaling and techniques to restructure data processing algorithms to reduce power requirements at the software level.

1.0.3. Background of sensor network:

Wireless sensor network(WSN) is a collection of micro-electromechanical system, sensor technology, embedded computing technology, information processing technology, modern network and wireless communication technology and digital electronics in the integration of a new generation of task oriented distributed network.

Sensor nodes offer a powerful combination of distributed sensing, computing and communication. The ever-increasing capabilities of these tiny sensor nodes, which include sensing, data processing, and communicating, enable the realization of WSNs based on the collaborative effort of a number of other sensor nodes. They enable a wide range of applications and, at the same time, offer numerous challenges due to their peculiarities, primarily the stringent energy constraints to which sensing nodes are typically subjected. The failure of any one node can change the entire system. In idle mode, the nodes consume almost the same amount of energy as in active mode. While in sleep mode, the nodes shutdown the radio to save the energy. Energy constraints end up creating computational and storage limitations that lead to a new set of architectural issues. In many cases (e.g. surveillance applications), it is undesirable to change the batteries that are depleted or of energy

As illustrated in Figure 1.1, each sensor node is consisting of five main components; a microcontroller unit, a transceiver unit, a memory unit, a power unit and a sensor unit. Each one of these components is determinant in designing a WSN for deployment. The microcontroller unit is in charge of the different tasks, data processing and the control of the other components in the node. It is the main controller of the wireless sensor node, through which every other component is managed. The controller unit may consist of an on-board memory or may be associated with a small storage unit integrated into the embedded board. It manages the procedures that enable the sensor node to perform sensing operations, run associated algorithms, and collaborate with the other nodes through wireless communication. Through the transceiver unit a sensor node performs its communication with other nodes and other parts of the WSN. It is the most power consumption unit. The memory unit is for temporal storage of the sensed data and can be RAM, ROM and their other memory types (SDRAM, SRAM, EPROM, etc.), flash or even external storage devices such as USB.

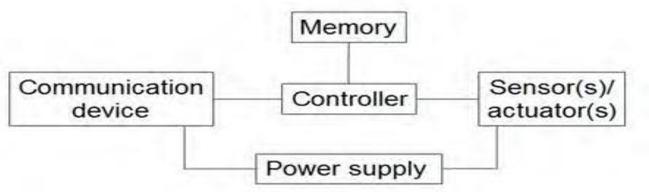

Figure 1.1 Components of a node of a WSN.

The power unit, which is one of the critical components, is for node energy supply. Power can be stored in batteries (most common) rechargeable or not or in capacitors. For extra power supply and recharge, there can be used natural sources such as solar power in forms of photovoltaic panels and cells, wind power with turbines, kinetic energy from water, etc.Last but not least is the sensor unit, which is the main component of a wireless sensor node that distinguishes it from any other embedded system with communication capabilities. It may generally include several sensor units, which provide information gathering capabilities from the physical world. Each sensor unit is responsible for gathering information of a certain type, such as temperature, humidity, or light, and is usually composed of two subunits: a sensor and an analog-to-digital converter (ADC). The analog signals produced by the sensor based on the observed phenomenon are converted to digital signals by the ADC, and then fed into the processing unit.

In WSNs, the sensor nodes have the dual functionality of being both data originators and data routers. Hence, communication is performed for two reasons:

• Source function: Each sensor node's primary role is to gather data from the environment through the various sensors. The data generated from sensing the environment need to be processed and transmitted to nearby sensor nodes for multi-hop delivery to the sink.

• Router function: In addition to originating data, each sensor node is responsible for relaying the information transmitted by its neighbors. The low-power communication techniques in WSNs limit the communication range of a node. In a large network, multi-hop communication is required so that nodes relay the information sent by their neighbors to the data collector, i.e., the sink. Accordingly, the sensor node is responsible for receiving the data sent by its neighbors and forwarding these data to one of its neighbors according to the routing decisions.

1.0.4. Future 5G Communication.

Device-to-device (D2D) communications is seen as new paradigm that will be implemented in the next generations of mobile networks to provide high performance in wireless network, improving coverage, provide spectral efficiency, high data rates and offer new peer-to-peer services with QoS guarantees. Direct communication will improve spectrum efficiency, overall system throughput, and energy efficiency, and decrease the delay between devices. It will enable new peer-to-peer and location-based applications and services. However the energy demand for IoT will increase dramatically in the near future considering the widespread interest and adoption of various organization, which will lead to higher carbon footprint and other environmental issues.

1.0.5. Transmitter receiver's concept

For actual communication, both a transmitter and a receiver are required in a sensor node. The essential task is to convert a bit stream coming from a microcontroller (or a sequence of bytes or frames) and convert them to and from radio waves.

The transmitter/receiver (TX/RX) pair operates at a frequency of 434 MHZ. A radio frequency (RF) transmitter receives a serial data and transmits it wirelessly through RF through its antenna connected. The transmitted data is received by an RF receiver operating at the same frequency as that of a transmitter. The encoder is used for encoding parallel data for transmissions while the reception is decoded by a decoder Most current energy minimization models focus on sending and receiving data (Wang et al., 2006a), while other parameters are neglected. In (Heinzelman et al., 2000) and (Heinzelman et al., 2002), the power consumption model focused on the cost of sending and receiving data and deduced the upper limit of the energy efficiency of single hop distance. This approach considers an intermediate node between source and destination so that the retransmission will save the energy. Other approaches evaluate the energy efficiency of wireless sensor networks by using the power consumption model mentioned in (Heinzelman et al., 2000) and (Heinzelman et al., 2002).To consume less energy, it is important to minimize the time and energy to switch between different modes and transmit and receive states (Raghunathan et al., 2002). Furthermore, a low-power listening approach may operate at the physical layer, in which the basic idea is to periodically turn on the receiver to sample the incoming data. This duty-cycle approach reduces the idle listening overhead in the network (Halkes et al., 2005). Moreover, the energy consumption of the radio channel for sending and receiving data is equal; consequently, energy efficient MAC protocols have to maximize the sleep time of sensors (Raghunathan et al., 2002). Due to real-time monitoring and interaction with different parts of a sensing node, the operating System (OS) is probably the best place to optimize and manage energy consumption of a WSN at the node level. Perhaps one of the best known techniques at the OS kernel level for minimizing energy consumption in the anode is processing unit scheduling by Dynamic Voltage-Frequency Scaling (DVFS). This technique allocates CPU time to tasks and manipulates the CPU power states (Sravan et al., 2007)**.** In other words, tasks are executed at different frequencies, where lower frequencies mean less power consumption, and the CPU is moved to the lowest power state when there is no task to execute.

A sensor consumes a large amount of energy during data transmission through three major activities: transmission, reception, and being idle. One study (Langendoen., 2003) showed that the ratio of power consumption in a processor (including CPU, memory) compared to the radio for the sensor nodes alters from 1:12.5 when both processor and radio are in sleep mode, to 1:4.76 when both are in active mode. As the largest energy consumer in a sensor, radio should play an important role in managing energy consumption and extending sensor lifetime.

1.0.6. Various Clustering Parameters

Some important parameters with regard to the whole clustering procedure in WSNs are:

• Nodes types and roles: In heterogeneous environments, the CHs are assumed to be equipped with significantly more computation and communication resources than others. In homogeneous environments, all nodes have the same capabilities and just a subset of the deployed sensors is designated as CHs.

• Multiple levels: In several published approaches the concept of a multi-level cluster hierarchy is introduced to achieve even better energy distribution and total energy consumption (instead of using only one cluster level). The improvements offered by multi-level clustering are to be further studied, especially when we have very large networks and inter-CH communication efficiency is of high importance.

1.1. PROBLEM STATEMENT.

Energy Consumption is one of the most fundamental and crucial factor determining the success of the deployment of sensors and wireless sensor networks (WSNs) due to many severe constraints, such as the size of the sensors, the unavailability of power source and inaccessibility of the sensor devices once they are deployed. Efforts have been made to minimize the energy consumption of wireless sensor networks and lengthen their useful lifetime using various approaches at different levels. Some approaches aim to minimize the energy consumption of the sensors itself at its operating levels (Min et al.,2001).some aim to minimize the energy spent in the input/output operation at the data transmission levels (Alzoubi et al,2002) and others target the formulation of sensors network in term of their topology and related routing mechanism (shah and Rabaey,2002).in addition to the minimization efforts, some approaches have tried to replenish the energy capacity of the sensors by building into their components and mechanism for harvesting additional energy from available energy sources within their environment such as solar, thermal or wind power source (Raghanathan and chon 2006) another approach is to scan systematically through the level of OSI network reference model and minimize energy consumption(Joaque et al 2007).

The sensor nodes are deployed in a distributed ad hoc manner to cooperate with each other to perform their task, by seamlessly integrating the WSNs, 5G will touch many scenarios in the future, such industrial automation, smart cities etc, however, state estimation, or signal reconstruction is a cornerstone in the aforementioned scenario. The major requirements that apply to most sensor network applications (Rabaey et al., 2000, H.Edgar and Callaway, 2004, Akyildiz et al., 2002b, Pottie and Kaiser, 2000): is Lifetime, it is desirable to prolong the lifetime of the network. Limited available energy makes the node lifespan a tremendous drawback of the wireless node technologies. Moreover, this limited energy may influence the robustness and/or reliability of the monitoring and/or control application built on top of the WSN

In this study a novel distributed state estimation algorithm to reduce the energy consumption is developed by looking into a compressive sensing technique (CS).which will improve energy efficiency by reducing the energy consumption of the WSNs and will bring green communication WSN system.

1.2. MAIN OBJECTIVE

Develop a stable distributed filtering algorithm for reconstructing the sparse signal in the discrete-time nonlinear stochastic system which utilizes advantages of compressive sensing and the square root decomposition technique to improve energy efficiency.

1.3. SPECIFIC OBJECTIVES.

1. Investigate Algorithms and distributed nonlinear state estimation problems in WSNs.
2. Develop algorithm for energy efficiate WSN's.
3. Test and validate the algorithm.

1.4. RESEARCH QUESTION.

1. What Algorithms and distributed non linear state estimation problem Exist?
2. Can this energy efficiate algorithm be for WSNs?
3. Can this algorithm be tested and validated?

1.5. SIGNIFICANCE OF THE STUDY

The ongoing concerns about environment and global warming, pose more challenges in meeting the increasing demand for deployment of wireless communication networks. The green communication (GC) has become a new trend in wireless communication network design and operation.

The intersection of the irredeemable trends namely escalating energy cost, and accelerated rise in communication usage, creates an urgent need to address the development of energy-efficient and environmentally-friendly use of the ICT facilities, for example Wireless Communication is the largest factor contributing to the wireless industryenvironmental impact with the emission from the telecommunication business sector estimated at between 0.5% and 1% of the whole world carbon footprint. Globally, electricity consumption by the ICT sector in 2012 was estimated to be roughly 900Million MWh, or 4.6% of the world's overall electricity consumption (Heddeghen et al.2014) .This includes electricity consumption by Data centers, Telecommunication and limited end user consumption.

1.6. MOTIVATION OF THE STUDY

The main object of green communication is to save as much as possible the energy consumption of the communication system. The ongoing concern about environmental and global warming, pose more challenge in meeting the increasing demand for deployment of wireless communication Network.

Most of the energy is consumed during the sensing data processing, data storage, and communication phases. Hence reducing the number of measurements by each sensor, means reduction in the data dimensionality of the mentioned phase, this will improve energy efficiency by reducing the energy consumption of the WSNs and will bring green practices to the 5G communication system.

1.7. SCOPE OF THE STUDY

From the perspective of 5G,a distributed nonlinear state estimation algorithm for WSN's is propose in this study that utilizes advantages of compressive sensing and the square-root decomposition technique to improve energy efficiacy.By embedding the pseudo-measurement technology into the cubature Kalman filter and corresponding information filter I will derive algorithm and its square-root version by using the QR decomposition. The distributed algorithm is developed by means of high-pass consensus filter.

CHAPTER TWO

LITERATURE REVIEW

2.0. INTRODUCTIONS

The infrastructure is the main source of power consumption from the service provider's perspective in WSNs. Distributed nonlinear state estimation in wireless sensor a network will be seamlessly integrated with the forthcoming 5G communication system. Implementations of WSNs have to address a set of technical challenge. Energy efficient wireless communications systems are being sought and are typical of WSNs. therefore, a novel distributed state algorithm to reduce the energy consumption is required. In the effort to provide energy efficiency, I will explore compressive sensing (CS) technique based on the revelation that a sufficient compressible or sparse signal can accurately be recovered from smaller number of measurements than the unknown. Specifically, the reconstruction performance of the distributed filter is expected to be comparable to the centralized counterpart where the measurements from the sensors are collected as a centralized measurement in fusion center.

2.1. WSN'S ENERGY CONSUMPTION

Power efficiency in WSNs is generally accomplished in three ways:

1. Low-duty-cycle operation.

2. Local/in-network processing to reduce data volume (and hence transmission time).

3. Multihop networking reduces the requirement for long-range transmission since signal path loss is an inverse exponent with range or distance. Each node in the sensor network can act as a repeater, thereby reducing the link range coverage required and, in turn, the transmission power.

2.1.0. Power Consumption of Communication Module.

Based on the structure and power consumption of each component, the total power consumption for transmitting and for receiving, denoted by P_T and P_R , are specifically given by:

$$P_T\,(d) = P_{TB} + P_{TRF} + P_A(d) = P_{TO} + P_{TO} + P_A(d) \qquad (1{:}1)$$

$$P_R = P_{RB} + P_{RRF} + P_L = P_{RO} \qquad (1{:}2)$$

Where;

$P_T\,(d)$, is the power consumption of the power amplifier which is a function of the transmission range, d.

$^{P_{TB}}/_{P_{RB}}$, is the power consumption in base band DSP circuit for transmitting or receiving (mW).

$^{P_{TRF}}/_{P_{RRF}}$ is the power consumption in front-end circuit for transmitting or receiving (mW).

P_L is the power consumption of LNA for receiving (mW).

Since P_{TB} and P_{TRF} do not depend on the transmission range, the two components can be modeled as a constant, P_{TO} . Similarly, the power consumption of the receiving circuitry can be modeled as a constant, P_{RO}, since P_{RB} and P_{RRF} are clearly not dependent on transmission range, and P_L is also a constant while assuming that the LNA is properly designed and biased to provide the necessary sensitivity to reliably receive, demodulate and decode a minimum power signal, P_{Rx-min} .

While there are many types of RF power amplifiers, the total power consumption of a power amplifier, PA (d), will depend on many factors including the specific hardware implementation, DC bias condition, load characteristics, operating frequency and PA output power, P_{TX} . A simple class a power amplifier is shown in Figure 2.

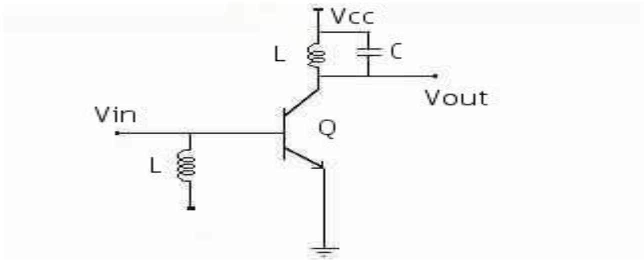

Fig 2:1.Simple class a power amplifier

The power amplifier delivers RF output power, P_{TX} , to the antenna/load. In general, the required RF output power, $P_{TX(d)}$ for reliable transmission will depend on the transmission range, d. The large inductance, BFL, feeds DC power to the drain of the transistor. The total power consumption of the PA is given by P_{dc} and is the same as P_A defined above. The ratio of RF output power to DC input power is called the drain efficiency (denoted as η) and is given by:

$$\eta = {}^{T_{TX}}/_{P_{DC}} \tag{1:3}$$

By definition, the drain efficiency of a PA will be less than 100%. For example, simple class A power amplifiers have a maximum drain efficiency of 50% as equal amounts of power are dissipated in the bias circuitry and in the load. The drain efficiency will typically vary when the output power delivered to the load changes. In particular, for most types of power an amplifier, the drain efficiency increases while P_{TX} is increasing and reaches its maximum value when P_{TX} reaches the maximum output power P_{Max} .

By combining the concept of drain efficiency with the formula described in the previous part of this section, the power consumption of the communication module can be modeled as:

$$P_T\,(d) = P_{To} + {}^{P_d}/_{\eta} \tag{1:4}$$

$$P_R = P_{RO} \tag{1:5}$$

2.1.1. Channel Model

The RF environment and communication channel are simply modeled by only considering path loss and by ignoring fading, multi-path and other more complex effects. Thus,

$$P_{Tx} = {}^{P_{Tx}}/_{(A \times d^{\propto})} \qquad (1:6)$$

Where $P_{Tx}$the RF power is delivered to the antenna by the PA of the transmitting sensor node and P_{Rx} will be the RF power received by the antenna of the receiving sensor node and delivered to the LNA.The parameter A is determined by the characteristics of the transmitting and receiving antennas. The path loss exponent is given by α and is about 2 for free space and will increase due to the presence of obstacles.

2.1.2. Basic power consumption model

Combining equations (1.4) and (1.5), we can determine the power consumption of the communication module for a given radio environment as follow;

$$P_T\,(d)\ = P_{To}\ + \frac{P_{Rx} \times A \times d^{\alpha}}{\eta} \qquad (1:7)$$

The SINR (Single-to-Interference and Noise-Ratio) requirements of the receiver determine the minimum required received power, P_{Rx-min}, for reliable communication. Thus, the minimum power consumption to reliably transmit data to another sensor node which is located at a distance, d, is given by:

$$P_T\,(d)\ = P_{To}\ + \frac{\varepsilon \times d^{\alpha}}{\eta} \qquad (1:8)$$

Where ε is a constant given by$P_{Rx-min} \times A$. Similarly, the power consumption of a sensor node to reliably receive data is a constant and is given by:

$$P_R = P_{RO} \qquad (1:9)$$

2.1.3. Multi-hop power consumption model.

In order to evaluate the power consumption model for a multi-hop network, a network model is needed. If we assume a channel model, which only includes path loss then a multi-hop routing scheme will perform the best in a simple 1-D linear WSN topology. The single-hop 1-

D linear WSN consist of a source node S and a destination node D separated by a distance R and a multi-hop 1-D linear WSN has an additional n-1 intermediate identical relay nodes intermediate identical relay nodes $N_{i,}$ *i*=1, …*n*-1 placed in a line from S to D. as shown in the figure below

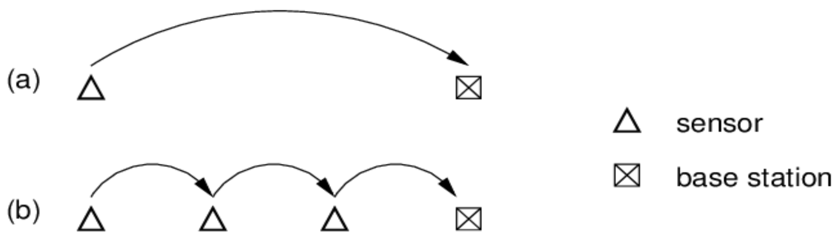

Fig 2.1.Network Model

P_R Describes the power consumption for receiving

$P_T\,(d_i)$ Denotes the power consumption for transmitting over a distance *d.i* is an integer from 1 to the total number of hops, *n*

$P_T\,(R/n)$ Denotes a power consumption for transmitting over a distance R/n, we use *P*(*n*) to denote the total power consumption for sending from S to D with *n*-hops.

We ignore the power consumption in the destination node D, because it is assumed to be connected to an external power supply and is not resource constrained. Based on the network model in fig above we obtain the Multihop power consumption model with arbitrary distance between nodes as follows;

$$P(n) \;= (n\;-1)P_{RO} + nP_{TO} + \frac{\varepsilon}{\eta}\sum_{i=1}^{n} d_i^{a} \qquad (2:0)$$

Similarly, based on the network model we can obtain the multi hop power consumption model with equal distance between nodes as follow;

$$P(n) \;= (n\;-1)P_{RO} + nP_{TO} + \frac{(n\times\varepsilon\times(R/n)^{\alpha}}{\eta} \qquad (2:1)$$

This model of WSN power consumption clearly shows in particular the dependency of the power amplifier performance (i.e. Drain efficiency, η).

The sensor nodes are deployed in a distributed ad hoc manner to cooperate with each other to perform their tasks, by seamlessly integrating the WSNs, 5G will touch many scenarios in the future, such as industrial automation, smart cities etc However, state estimation, or signal reconstruction is a cornerstone in the aforementioned scenario. On the other hand, the distributed estimation schemes are becoming increasingly popular in WSNs community due to their high fault tolerance and scalability for large –scale dynamical system with distributed measurements over large geographical area.

Unlike the centralized scheme, the distributed schemes usually rely on device to device communication among sensor nodes and the information fusion task is distributed among multiple sensor nodes without the infrastructure (fusion center).

The infrastructure is the main source of power consumption from the service provider's perspective in WSNs.therefore, it is essential to explore a novel distributed state algorithm to reduce the energy consumption.

In the effort to provide energy efficiency, I will explore compressive sensing (CS) technique based on the revelation that a sufficient compressible or sparse signal can be accurately recovered from smaller number of measurements than the unknown.

2.2. FUNDAMENTALS OF ALGORITHM

2.2.1. Compressive Sensing

Compressive sensing theory states that a signal can be sampled without any information loss at a rate close to its information content. Compressive sensing relies on two fundamental properties: Signal sparsity and incohence.signals are represented with varying levels of sparsity indifferent domain. For example, a single tone sine wave is either represented by a single frequency coefficient or by an infinite number of time domain samples. Consider a real-valued, finite length, one-dimensional, discrete signal *x*, which we view as an,

$N \times 1$ column vector in R^{N} with elements $\chi(n), n = 1,2 \cdots\cdots N$, We treat the image or higher-dimensional data by vectorizing it into a long one-dimensional vector.

Any signal in R^N can be represented in terms of a basis of $N\times 1$ vector $\{\psi\}_{i=1}^{N}$. For simplicity, assume that the basis is orthonormal.Forming the $N \times N$ basis matrix $\psi[\psi|\psi_1 \cdots\cdots |\psi_n]$:

By stacking the vector $\{\psi_i\}$ as columns, we can express any signal;

$$\chi = \sum_{i=1}^{N} S_i\,\psi_i \text{ or } \chi = \psi_s \qquad (4:3)$$

Where s is the N×1 column vector of weighting coefficients $s_i = \langle \chi; \psi_i \rangle = \psi_i^T \chi$ and where T denotes the transpose operation. Clearly, x and s are equivalent representations of the same signal, with x in the time domain and s in the ψ domain.

I will focus on a signal that have a sparse representation, where x is a linear combination of just K basis vectors, with $K \ll N$.That is, only K of the S_i in (22) are non zero and $(N-K)$ are zero. Sparsity is motivated by the fact that many natural and manmade signals are compressible in the sense that there exists a basis $\psi \,\epsilon\, R^{N\times N}$ Where the representation (4:3) has just a few large coefficients and many small coefficients.

Compressible signal are well approximated by K-sparse representations: this is the basis of transforming coding. For example, natural images tend to be compressible in the discrete cosine and wavelet bases on which the JPEG and JPEG-2000 compression standard are based.

Transform coding plays a central role in data acquisition systems where the number of samples is high. in this frame work, we acquire the full N-sample signal x;compute the complete set of transform coefficients $\{s_i\}$ via $= \psi^T x$;Locate the K largest coefficients and discard the $(N-K)$ smallest coefficiates;and encode the K values and location of the largest coefficients.

NB/ Sparsity. A signal is called sparse if most of its components are zero. As empirically observed, many real-world signals are compressible in the sense that they are well approximated by sparse signals

2.3. SPARSE REPRESENTATIONS

For sparse data, only the non-zero coefficients need to be stored or transmitted in many cases; the rest can be assumed to be zero. Mathematically:

We say that a signal *x* is *K*-sparse when it has at most *K* non-zeros, *i.e.*, $\|x\|_0 \leq K$. We let

$\sum_k = \{x: |x|_0 \ \leq \mathrm{K}\ \}$ (4:4)

Denotes the set of all *K*-sparse signals. Typically, we deal with signals that are not themselves sparse, but which admit a sparse representation in some basis ψ . In this case we will still refer to *x* as being *K*-sparse, with the understanding that we can express *x* as $x = \psi_\alpha$ where 0 $\alpha \leq K$.

Sparsity has long been exploited in signal processing and approximation theory for tasks such as compression. Sparsity also has been exploited heavily in image processing tasks, since the multi scale wavelet transform provides nearly sparse representations for natural images. As an example of one-dimensional (1-D) signal that has different signal sparsity consider the signal.

$x(t) = 10\sin(20\pi t/1000) - 5\sin(60\pi t/1000) + 4\sin(100\pi t/1000)$ (4:5)

Where $1 \leq t \leq 1000$. $1 \leq t \leq 1000$

One can interpret sampling as a basis expansion where the elements in the basis are impulses placed at periodic points along the time axis. In this case, the dual basis consists of sinc functions used to reconstruct the signal from the discrete-time samples. This representation contains many non-zero coefficients, and due to the signal's periodicity, there are many redundant measurements. Representing the signal in the Fourier basis, on the other hand, requires only two non-zero basis vectors, scaled appropriately at the positive and negative frequencies. Applying the Discrete Cosine Transform (DCT) to the signal, shows that only 335 nonzero

DCT coefficients represent the signal $x(t)$. Similarly, applying the Discrete Wavelet Transform (DWT) to the signal shows that only 265 non-zero DWT coefficients represents the signal $x(t)$ illustrates the four basis expansions that yield different levels of sparsity for the same signal $x(t)$.

An important assumption used in the context of compressive sensing is that signals exhibit a degree of structure. Here, it is important to note that there is a difference between signal sparsity and signal compressibility. The signal is considered sparse if it has only a few non-zero values in comparison with its overall length. However, it is considered compressible if it's sorted coefficient magnitudes decays rapidly.

To consider this mathematically;

Let *x* be a signal which is compressible in the basis $\psi, x = \psi_{\alpha}$, (4:6)

Where α are the coefficients of *x* in the basis ψ. If *x* is compressible, then the magnitudes of the sorted coefficients observe power law decay;

$|\alpha_s| \leq C_s s^{-q}, s = 1,2,\cdots,$ (4:7)

A signal is defined as being compressible if it obeys this power law decay. The larger q is, the faster the magnitudes decay, and the more compressible a signal is.

2.4. THE CONCEPT OF COHERENCE

Concept of coherence is extensively used in the field of sparse representations of signals. In particular, it is used as a measure of the ability of suboptimal algorithms such as matching pursuit and basis pursuit to correctly identify the true representation of a sparse signal. Current assumptions in the field of compressed sensing and sparse signal recovery impose that the measurement matrix has uncorrelated columns. To be formal, one defines the coherence or the mutual coherence of a matrix A is defined as the maximum absolute value of the cross-correlations between the columns of A.

Formally, let $a_{1,}a_{2.}\cdots\cdots a_n$ be the columns of the matrix A, which are assumed to be normalized such that $a_i^T a_i = 1$. the mutual coherence of A is then defined as;

$$\mu(A) = \max_{1\leq i\neq j\leq m}\left|a_i^T a_j\right| \qquad (4:7)$$

A lower bound is

$$\mu(A) \geq \sqrt{\frac{N-d}{d(N-1)}} \qquad (4:8)$$

We say that a dictionary is incoherent if $\mu(A)$ is small. Standard results then require that the measurement matrix satisfy a strict incoherence property, as even the RIP imposes this. If the dictionary D is highly coherent, then the matrix AD will also be coherent in general.

Coherence is in some sense a natural property in the compressed sensing framework, for if two columns are closely correlated, it will be impossible in general to distinguish whether the energy in the signal comes from one or the other. For example, imagine that we are not under sampling and that A is the identity so that we observe $y = Dx$.Suppose the first two columns are identical, $d_1 = d_2$. Then the measurement 1 d can be explained by the input vectors $(1,0,\cdots\cdots 0)$ or $(0,1\cdots\cdots 0)$ or any convex combination. Thus there is no hope of reconstructing a unique sparse signal x from measurements$y = ADx$. However, we are not interested in recovering the coefficient vector x, but rather the actual signal Dx.

2.5. THE KALMAN FILTER

The Kalman filter (KF) is an efficient recursive filter that estimates the state of a linear dynamic system from a series of noisy measurements.

During the past few years, huge efforts have been made to develop efficiate filters for nonlinear and non-Gaussian systems. The Bayesian probabilistic inference provides an optimal solution framework for dynamic state estimation problem, but the solution requires propagating the full density function (PDF), which makes researchers give up obtaining the optimal filters analytically. As a consequence, some approximations, in the Bayesian framework, have been adopted to develop the suboptimal numerical filtering techniques.

When confronting nonlinear filtering problems, the first commonly used approach is to linearize.the extended Kalman filter (EKF) which has been used as the state-of-the art filter in many engineering areas, typically applies the KF to nonlinear dynamic systems by simply linearizing the entire nonlinear model, thus trying to avoid the nonlinear aspects of such problems. The EKF can give particularly poor performance if the dynamics systems are highly nonlinear.

As a better alternative to the EKF, a large number of non linear filter based on the idea of Bayesian sampling strategies deterministic sampling and random sampling. The former includes the unscented Kalman filter (UKF),the Gaussian Hermite filter (GHF),the central difference filter (CDC) etc.

This types of filter utilizes the Gaussian assumption to approximate in PDF.A well-known filter using random sampling is the particle filter (PF),which also include the Gaussian particle filter (GPF),the quasi-Gaussian particle filter (GPF),the quasi-Gaussian particle filter (QGPF) etc.These filters approach PDF by using a certain number of particle.

The Kalman filter provides an efficiate recursive estimator for the unobserved state of linear discrete time dynamical system in the presence of measurement error. Kalman (1960) first introduced the method in the engineering literature, but it can be understood in the context of Bayesian inference. The Kalman Filters is similar in nature to the standard linear regression model. The state of the process s_t corresponds to the regression coefficient; however the state is not constant over time, requiring the introduction of the transition equation

Let y_t denote a vector of observed variable at the time *t* and let s_t denote the unobserved state variable of the system at time *t*. I wish to conduct inference about the state variable given only the observed data $\{y_t\}$ and the structure of a linear model consisting of measurement equation and transition equation

The evolution of the observed variable depends on the state variable through a linear measurement equation.

$$y_t = Fs_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, \mathbf{\Omega}_\varepsilon) \tag{4:9}$$

The variable y_t is observed with measurement error which follows the Normal distribution with zero and co-variance matrix $\mathbf{\Omega}_\varepsilon$.

The state vector s_t obeys transition equation.

$$s_t = Gs_{t-1} + \eta_t \sim N\left(0, \mathbf{\Omega}_\eta\right) \tag{5:0}$$

Where;

G and $\mathbf{\Omega}_\eta$ are known matrices and η_t Captures the influence of effects that are outside the model on the state transition process. The noise terms ε_t and η_t are independent. In general G and F can be time-dependent but for the sake of simplicity the time subscripts are omitted here.

2.6. THE CS-EMBEDDED KF

The CSKF algorithm is aimed at solving a stochastic CS problem of the form.

$$\min_{\hat{z}_k} E_{z_k|\gamma_k} [\|z_k - \hat{z}_k\|_2^2 \quad] s.t. \|\hat{z}_k\| \ _1 \leq \epsilon' \tag{5:1}$$

It can be shown that for both proper values of the tuning ϵ' and ϵ, the solution of both 4:3 and the convex l_1 relaxation of concide.The nonlinear in-equality constraint in (4:3) is readily treated within the conventional KF framework using a so-called pseudo-measurement (PM) technique. In practice this is carried out by recasting this constraint as.

$$0 = \bar{H}_{k^{z_k}} - \epsilon', \bar{H}_k := \mathrm{sign}(z_k) \tag{5:2}$$

Where $\mathrm{sign}(z_k)$ denotes a row vector consisting of the sign of the entries in z_k.This formulation facilitates the implementation of the standard KF update equation which are provided in algorithm 1 for the sake of completeness. Notice that this approach assumes that ϵ' is random quantity, specifically a zero-mean Gaussian random variable with variance σ^2.

2.7. RELATED STUDIES

A historical summary of the energy conditions is maintained using the relation;

$$\bar{x}_k = \alpha\bar{x}_{k-1} + (1-\alpha)\bar{x}_k \quad (3:1)$$

Where;

α is the weighted factor

$\bar{x}_k$ is the energy generated in a slot.

$\bar{x}_{k-1}$ is the historical average of the previously stored energy.

In 2008, David D. L. developed a mobile host, which is capable to wirelessly transfer electrical energy on a 2.4 MHz signal to charge nodes in remote locations. The mobile host is also capable to collect sensing data from the deployed nodes. A test-bed is implemented using a helicopter mounted node. For an assumed distance of two meters, and assuming no losses, attached capacitors are charged in no less than 12 seconds. The transmission and receiving antennas used in the experiment are of the size of the order of 18.7 × 3 and 15 × 15 inches respectively. Although, this effort explored a new path towards the possibility of charging a node in the field, but using such bulky platform is infeasible in sensor networks due to their limited size and cost requirements. The above effort poses no concern regarding the overhead in terms of size and cost of the sensor node. Increase in the distance between the transmitter and receiver increases the charging duration, reducing the overall efficiency of the system.

Some similar efforts on wireless charging of nodes are proposed using off the shelf devices, in order to improve sensor network lifetime. The wireless energy is transferred through electromagnetic waves to sensor nodes equipped with rechargeable batteries. Several experiments were carried out to investigate the effect of distance and location of nodes on the energy transfer. It was observed that when the distance between the transmitter and receiver is increased beyond 12 meters, it takes almost infinite time to charge a particular node. It is also observed that with efficient placement of nodes, the charging time can be substantially reduced.

An energy charging cycle aware routing algorithm is proposed by modifying the existing Ad-hoc On Demand Routing (AODV) routing protocols, since typical routing metrics based on shortest path are not applicable in energy harvesting networks.

The route request (RREQ) packet includes;

$T_{ch}^{max}(k)$ the maximum charging time of all nodes traveled on path κ, (k) and $\eta_c{}^{max}(k)$,the observed standard deviation of this maximum value. Each node i along the path update the RREQ with its respective charging time in case it's greater than the existing.

The destination node selects the minimum charging time path among the available paths.

$$\psi = min\{T_{ch}{}^{max}(K)\}, \forall\, \kappa \qquad (3:2)$$

$$\psi = min\{max[t_{ch}{}^{i}]\}\ \forall\, i \in path\ k, \forall\, k \qquad (3:3)$$

An optimization framework is proposed to address the trade-offs of the charging and transmission duration, since both occurs in the same frequency band. The base station selects the optimal path, and replies Route Reply (RREP) to the corresponding nodes with the charging time t_{ch} and transmission time $T_x$common to all of the nodes along the path. The optimization framework returns the charging duration t_{ch} and frame length $T_{frame} = T_x + T_{ch}$.Therefore, the source nodes upon receiving the RREP then begins forwarding the packets. The optimization framework is described below;

Given:

$$L_{lim}, ERS_{lim,} N, \qquad (3:4)$$

To find:

$$T_{ch}, T_{frame} \quad (3:5)$$

Maximize Throughput = $\frac{T_x \cdot R}{T_{frame}}$ (3:6)

Subject to:

$$(E_{rec} - E_{idle}) \cdot T_{ch} - E_{tx} \cdot T_x > 0, \quad (3:7)$$

$$N\left(T_{ch} + \frac{P+H}{R}\right) \leq L_{lim} \quad (3:8)$$

$$\frac{1}{ESR_0}\left[1 - k \cdot t \cdot e^{\frac{-4700}{T+273}}\right] > \frac{1}{ESR_{lim}}, \quad (3:9)$$

$$T_{Frame} = T_x + T_{Ch} \quad (4:0)$$

For *N* number of nodes in the path, throughput is defined as the ratio of the number of bits sent during T_x to the frame length T_{Frame}. To maximize the throughput, the constraints are also defined, where E_{Rec} is the energy receiving rate from the wireless charger and E_{Idle} is the sensor node's idle energy during charging time. E_{tx} is defined as the rate, at which a sensor node losses energy during transmission. Similarly, *P* is the packet size, *H* is the header size and *R* is defined as the sending rate of the data at the *N* hop route.

The constraints are explained below:

• The first constraint in ensures that the sensor is alive after each frame duration. The sensor expends E_{idle} during its charging time while it receives energy at the rate E_{Rec} from the wireless transmitter in timeT_{ch}. It also loses energy E_{tx} during transmission as mentioned above, thus, the residual energy should at be at least greater than 0.

• The second constraint in states that the end-to-end packet latency for the *N* hop route should be less than a pre-decided limit L_{lim}. In the worst case, a sensor may experience a delay equal to the charging timeT_{ch}, where no data can be sent and the transmission delay, given as the ratio of the packet size *P* with the header size *H* and the sending rate *R*.

• The Equivalent Series Resistance (ESR) in is a metric which determines the quality of capacitor operation. The capacitors are considered dysfunctional once the end-end latency limit L_{lim} is exceeded. L_{lim} and the capacitor quality metric ESR_{lim} are dependent on the application requirements. The T is the absolute temperature in Kelvin, at which the capacitor operates. Similarly, t is the operational time and k is a design constant.

• The constraint in (7) provides the relationship between the charging and transmission times and the frame time.

The performance evaluation highlights the following situations:

1. When L_{lim} is too small, either the node will not be able to charge enough or it may not be alive after each transmission.

2. By considering values of the charging time lower than the optimal derived T_{ch}, the network throughput is substantially increased. However, the rate at which the throughput increases exhibits a non-linear behavior, thus hinting that for sudden high bandwidth needs, decreasing the recharging time (thereby increasing the transmission time) will not incur a proportionally high degradation of lifetime. Moreover, we also observed that different packet sizes do not significantly impact the performance.

Several algorithms are proposed, in which nodes adjust their duty cycle by alternating between sleep and wakeup modes to reduce battery consumption. The idea is to set the node in a low power mode when there is no data communication in progress. In this way, energy wastage is avoided as the nodes only wakes up when there is a need of radio transmission or reception. Such algorithms can prolong the overall network lifetime by utilizing the battery only when they are awake.Xu et al (Xu et al,.2003) mentioned a number of challenges, including duty cycle control of redundant nodes, connectivity maintenance, self configuring and redundancy identification in a localized and distributed fashion. Duty cycle based algorithms can be further categorized as Topology control protocols, Sleep/wake-up protocols and MAC protocols with low duty-cycles. Topology control Protocols refers to schemes that adapts dynamic network topology in accordance to the application requirements. The aim is to set some nodes in sleep mode while keeping the network operational, hence prolonging network lifetime. Such protocols can be further divided as location driven and connectivity driven. In Location driven approaches, nodes are set to sleep or wake-up mode on the basis of their location. The location of the nodes are assumed to be known so that nodes can coordinate with each other to decide, which node in a particular area should be turned on, while not compromising coverage of that particular area.

Topology control schemes aim to reduce the topology and maintain it for topology conservation. Most of the efforts in this domain lie in the area of Connected Dominating Set (CDS) or backbone, which aims to form a reduced topology working on behalf of other nodes in the network. In this area, the authors proposed CDS Rule K algorithm that uses marking and pruning rules for exchanging neighbors list among a set of nodes. In CDS Rule K, a node remains marked as long as there is at least a pair of unconnected nodes in its neighbors; it is unmarked when it finds that all its neighbors are covered with high priority. Similarly, Energy Efficient CDS (EECDS) algorithm is proposed in, which also follows a two phase topology control scheme in order to form a connected dominating set based on coordinated reconstruction mechanism to prolong network lifetime and balance energy consumption. On the other hand, the authors in proposes A3 and A1 algorithm which constructs a backbone or a CDS in a single phase while in, the authors propose Poly algorithm, which provides reliability in addition to energy efficiency by constructing a backbone in a single phase. For evaluation of topology control algorithms, we used Attaraya simulator that has been specifically designed for WSNs. The Attaraya underlying features provide many advantages which includes, different energy and communication models, energy and node location distribution resources that can adapted according to the requirement in the simulations. On the other hand, the performance of the algorithms was evaluated under two metrics namely energy overhead and residual energy. The former shows the overhead associated or the energy consumed during the exchange of the messages, while the latter shows the remaining energy at the end of Topology Control operation. For evaluation of the algorithms under discussion, the nodes were distributed in an area of 600m × 600m while varying the node density from 50 to 250 nodes. Similarly, the algorithms were also evaluated for indoor Grid H-V and H-V-D topologies. In Grid H-V and H-V-D, nodes communicate with their horizontal, vertical and diagonal neighbors depending upon the topology deployed. The transmission radius and initial energy level of each node are set to 42m and 1J, respectively. The actuation energy equals 50nJ/bit while the communication energy is 100PJ/bit/m2. All the results were averaged over 100 simulations runs and the nodes energy distribution follows a uniform process while the node location distribution follows a random process.

The results demonstrate that the schemes using two phase backbone topology construction mechanism incur more energy overhead due to the use of large number of messages, while the schemes constructing backbone in a single phase incur less energy overhead. Similarly, the residual energy is also remains high for schemes with single phase mechanism for the same reasons mentioned earlier and therefore provides better energy efficiency.

Hyper-graph theory based topology control algorithm to replace simple graphs in large scale WSNs. Simple graph theory based algorithms results in high computational complexity and usually requires large solution space to manage large scale WSNs due to their small granularity. The transmission paths computed using traditional graph theory techniques provide lower fault tolerance due to unattended sensor nodes operations and unreliable wireless transmission channels. To maintain the connectivity of a delivery path, lots of control message to are required. Such control messages uses more bandwidth with increased energy consumption. (Zhang el al 2013) proposed a topology management algorithm called ESRAD.

Bhattlachaya el al (Bhattachaya and Kuman, 2014) presented algorithm that generates the minimum length multicast tree to send the minimum length multicast tree to data from one node to multiple sinks in WSNs Named towards source time (TST) algorithm if focuses on the minimization of number of hops, one of the most important factor in Wireless sensor network by producing an efficiate multicast tree with a low complexity.

The issue of limited solution space is addressed by using variable scale hyper edges. Similarly, the use of mutual back-up delivery paths in a single hype edge improves the fault tolerance capability. Comparison results with simple flooding, Directed Diffusion, EADD and Enhanced Fault Tolerant

Besides topology control algorithms, energy efficient routing algorithms such as AODV, Directed Diffusion, SPEED and Reliable Energy Aware Routing protocol (REAR) also ensure minimum energy consumption at relay nodes. Recently research focus is shifted toward energy efficient fault tolerant routing algorithms. One such algorithm DLS (Dynamic local stitching) is proposed recently in. DLS aims to repair broken transmission paths in WSN, specially, in harsh environments comprising unattended sensor nodes with unreliable wireless transmission channels. Unlike typical routing algorithms such as AODV, ENFAT-AODV, Directed Diffusion, SPEED and REAR which reroute the entire paths. DLS only repairs broken fragments of the original path, thus minimizing energy consumption as well as the recovery delay.

Geographical Adaptive Fidelity (GAF) and Geographical Random Forwarding (GeRaF) are typical examples based on location driven approaches. Muzznicki et al., 2012) after categorizing the most common WSN multicast procedure based on the geographic position of a target group. The author presented algorithm based on Dijkstra for discovering the shortest energy efficiate path via nodes that provide the maximum geographical advance toward sinks.Aman Kansal et al., 2010 proposed environmental energy availability method for power management algorithm. Harvesting energy load in anode.

The protocols such as Span and Adaptive Self Configuring sensor Networks Topologies (ASCENT) are examples of efforts implementing such approach. These efforts although demonstrated that topology control protocols provide better efficiency in terms of increasing network lifetime but efforts are still required to couple such protocols with other energy conservation protocols for perpetual network operation.

Duty cycling protocols can also be further classified on the basis of power management by adapting different sleep and wake-up protocols or MAC protocols having low duty cycles. For better understanding, sleep and wake-up protocols are further divided into on-demand, scheduled rendezvous and asynchronous protocols. On-demand protocols are used in event driven scenarios, where nodes should only wake-up when they are needed for communication. Typical Examples of such schemes are Sparse Topology and Energy Management (STEM), Pipeline Tone Wake-up (PTW) and Radio Triggered sleep wake-up schemes. The issue related to informing a sleeping node to wake-up is addressed by using multiple radios. A low rate and low power radio is used for signaling and a more power consuming radio is used for data communications. It seems to be ideal protocol but radio triggered wake-up scheme is not a feasible solution. It can only be applied in situations where nodes are in close proximity to each other. In addition, using a second radio seems to be an unrealistic approach. In scheduled rendezvous, nodes wake-up according to a schedule and remain active for a short period and then enter sleep mode till the next rendezvous time arrives. Such protocols are convenient, although, synchronization is required between the nodes. Such scheme also poses a drawback in terms of additional synchronization overhead. In asynchronous protocols, a node can wake-up independently of others and can still be able to communicate with its neighbors. It is easier to implement and ensures network connectivity even in highly dynamic conditions. Asynchronous protocols are said to be less energy efficient, therefore, consequently resulting in higher duty cycles than synchronous nodes.

An alternative duty cycling approach is by applying MAC protocols with low power consumption. These can be classified as Time Division Multiple Access (TDMA) based, contention based and hybrid MAC protocols.

In TDMA based protocols, nodes duty cycle is enabled only when channel access is required. A fixed time slot is assigned to each node and the energy consumed is reduced to only the respective time slot. The protocols such as Traffic-Adaptive MAC Protocol (TRAMA), Flow Aware Medium Access (FLAMA) and Lightweight Medium Access Control (L-MAC) are the most common ones adapting such schemes.

The TDMA based schemes provides efficiency in terms of energy consumption, since nodes turn on their radios only in their own allotted time slot (Ibrahim M. M. El Emary, 2013). These protocols provides limited flexibility and are generally scalable, however, they often requires tight synchronization and are very sensitive to interference. These protocols perform worse than contention based protocols in low traffic conditions and are therefore, rarely used in WSNs.

The contention based protocols on the other hand, achieves duty cycling by integrating medium access functionality with sleep or wake-up process. The most common schemes based on this principle are Berkeley MAC (B-MAC), Sensor MAC (S-MAC) and Data gathering MAC (D-MAC). These protocols are robust and scalable and maintain lower delay than TDMA based protocols, however, they results in high energy consumption due to contention and collisions. The hybrid a scheme refers to algorithms combining properties from both, TDMA based and contention based schemes. It behaves as contention based scheme when the level of contention between nodes is low, and then switches to TDMA based scheme when the level of contention is higher. These are complex schemes and are feasible only in situations where high numbers of nodes are deployed. The Zebra MAC (Z-MAC) and Hybrid MAC (HYMAC) are popular hybrid scheme combining strengths of TDMA based and Carrier Sense Multiple Access (CSMA) based schemes. Dynamic duty cycling is also applied by few researchers for harvesting enabled sensors. The energy allocation to the application is based on the availability of daily harvested energy. Kansal A. provided an adaptive duty cycling scheme for the energy harvesting sensor node in Moreover, Dynamic Power Management (DPM) algorithms can also be used to efficiently manage energy for a sensor node. In DPM, the sensor node is turned on when there is no sensing activity and triggered in case of occurrence of any event. Such algorithms mostly suffer from the overhead of sleep state transitions, specifically, in storage and retrieval of the sensor processing state during switching. Similarly, Dynamic Voltage-Frequency Scaling (DVFS) can also be adapted to manage the node energy consumption. DVFS schemes allow the node to operate at the maximum processing speed if the stored energy is sufficient; otherwise, the system reduces the execution of sensing tasks in order to conserve energy. The efficiency of such schemes to save energy depends on the application requirements for task execution. Energy conservation for longer network operation is only possible when sensing requests by the application are less frequent.

Data driven approaches are generally focused to reduce the amount of sampled data while keeping sensing accuracy within the acceptable level. Such approaches can be classified as data reduction schemes and energy efficient data acquisition. The data reduction schemes address the case of unneeded samples. The data prediction is a further classification of data reduction schemes, which are focused on building an abstraction of the sensed data, or in other words, a model for future data prediction. The data prediction schemes can be further divided into stochastic approaches, time series forecasting and algorithmic approaches. The stochastic approaches works on the principle of stochastic characterization of the phenomena as proposed in the Ken solution. Such protocols are involved in high-level computations such as aggregating, with the expense of high computational costs. These approaches are feasible in situations where powerful sensor nodes are available in the network, thus requires larger battery size. In time series forecasting, set of historical values are obtained by periodical sampling, which are then used to predict a future value in the same series. The most common techniques using these approaches are Moving average (MA), Auto-regressive (AR) or Auto-regressive moving average (ARMA) methods. This scheme is simpler and lightweight in implementation and provides satisfactory results in terms of accuracy. Examples of such approaches are Probabilistic Adaptable Query system (PAQ) and Similarity based Adaptive Framework (SAF) [98, 99]. In algorithmic approaches, heuristic or state transition model describing sensed phenomena are used. Typical examples of such approaches are Prediction based Monitoring in Sensor Networks (PREMON) and Energy Efficient Data Collection (EEDC). These techniques are considered case by case as they are more application specific schemes. In addition, few energy prediction algorithms and dynamic duty cycling based on the available harvested energy are proposed in Energy efficient data acquisition protocols are more focused towards reducing energy consumption of the node sensing subsystem. Such protocols assume that greater amount of energy is consumed by the sensing sub system of the node than the communication subsystem. These schemes are further divided as adaptive sampling, hierarchical sampling and model based active sampling. In adaptive sampling, the main focus is to reduce the amount of data to be acquired from the transducer based on either spatial or temporal correlation between data. These schemes are more general and efficient, and mostly implemented in a centralized fashion, thus requiring high computations. In hierarchical sampling, different types of sensors are installed on nodes. These schemes are more energy efficient, but are more application specific. However, the cost associated with the extra transceiver can be considered as a drawback of such schemes. The model based approaches are similar to data prediction schemes. The goal is to reduce the number of data samples by using computed models and saving energy, Adaptive Sampling Approach to Data Collection (ASAP), and Utility Based Sensing and Communication (USAC) are based on such schemes.

Mobility based energy conservation can be achieved by considering few mobile nodes in the network. These mobile nodes can be of two types, based on their behavior. They can either be part of the network infrastructure in which their mobility is fully controllable or generally a robotized one. Such nodes may follow a predictable pattern of mobility. On the other hand, they can be part of the environment, in which nodes mobility is uncontrollable and unpredictable. However, in some cases they might follow a mobility pattern that is neither predictable nor random in general. Mobility based algorithms can be further divided in two categories. A mobile sink based approach, in which a mobile sink is used to collect data from source nodes in the field in order to increase network lifetime. It is shown that using mobile sinks nodes can improve networks lifetime by 5 to 10 times than using static sink nodes. However, the possibility of latency associated with the data arrival at the sink node should be taken into consideration. Some examples of such approaches are Greedy Maximum Residual Energy (GMRE) , Two Tier Data Dissemination (TTDD) and Scalable Energy-efficient Asynchronous Dissemination (SEAD) protocol. In a mobile relay based approach, message ferries are used for data collection from source nodes. These message ferries moves in the field to collect data, carry the stored data and forward it to the destination node. Mobile relays have almost similar functionality as in data Mobile Ubiquitous LAN Extension (MULE) approaches, where the vehicles periodically visit a network to collect data. However, some issues needs to be addressed such as the sensors have to be continuously in wake-up mode while waiting for the MULE to arrive for data collection. The transmission schedule need to be defined to address the issue of the amount of time a MULE has to wait for data coming from the static nodes, and vice versa, when a sensor should transmit gathered data to the mobile element. Typical example of mobility based approaches is Zebra Net.

Energy efficient network operation is also possible by defining several application layer protocols. Typical application layer protocols can be categorized into three types; Sensor Management Protocols (SMP), Task Assignment and Data Advertisement protocols (TADAP) and Sensor Query and Dissemination protocols (SQDDP).

- Sensor Management Protocols (SMP) are used by network administrators to configure nodes to perform various tasks. These protocols can be used to introduce rules regarding data aggregation, time synchronization, sensor movements, clustering, authentication and key distribution.
- Task Assignment and Data Advertisement protocols (TADAP) are used to handle user's interests and sensor node advertisements. The users query for the sensing data they are interested and the corresponding sensor nodes advertise the requested data. TADAP provides the user software with efficient interfaces for interest dissemination which also supports energy efficient lower-level operations.
- Sensor Query and Dissemination protocols (SQDDP) are designed for attribute or location based sensor query. Typical example of such query could be for the location of all the nodes sensing temperature higher than a certain threshold, where the threshold can be defined by the user. These protocols are helpful in ensuring messages exchange between the user and the sensor deployed in the field under different conditions.

Among all the energy conservation schemes, topology control schemes which are based on duty cycling are the most recent and provide better energy efficiency and longer network lifetime. However, most of the current efforts are focused only towards energy conservation based on efficient energy consumption. Energy efficient designs of sensor hardware, software, algorithms and protocols have served well, but they eventually surrender when the attached batteries are drained. For instance, an energy-efficient protocol which relies on duty cycling of spatio-temporal sensing activities may result in application performance degradation for the sake of longer network lifetime.

This review is more focused towards identifying the potential of various alternate energy sources and the different efforts on their efficient utilization. Networks wide energy efficient protocol can better manage its operation while taking into account the nodes' supply and consumption. Research can consider both, the energy supply as well as the energy consumption in parallel while designing an energy efficient algorithm. Alternative energy sources from ambient environment and wireless transference based algorithms still require further improvements. Existing sources requires improvement regarding their energy harvesting efficiencies as well considering the possibility of exploring new sources. A hybrid technique comprising all the three existing sources (batteries, ambient environment, and wireless transfer) can also be considered to increase the network lifetime.

The comparison of energy consumption between chain, grid and random topologies was studied in (Qiong et al., 2013) the comparison revealed that grid topology had the highest energy consumption followed by random and chain topologies. Chain topology also showed better packet delivery rate than the other infact, grid topology had the most performance in both energy consumption and packet rate.

2.7.4. Consensus-based sparse signal reconstruction algorithm for wireless sensor network

Average –consensus algorithm have lately investigated as a family of low-complexity interactive distributed algorithms where a sensors in a group communicate with each other to reach consensus. In a more detail, each sensor receives information from others and adjusts their own information state with the goal to reach an agreement in a scalable and fault-tolerant manner. Consensus was initially elaborated in (TsitSikklis el al 2013).and has received a considerable attention in many subjects due to its wide range of applications such as load balancing in parallel calculation, coordination of autonomous agents, distributed control and data fusion.

A distributed sparse signal reconstruction algorithm using probabilistic graphical models in the Bayesian framework. First the three global information quantities are particularly designed for distributed sparse Bayesian inference by centralized update equations. Then, several average-consensus iteration is needed to reach a consensus on global information quantities in each local variational Bayesian (VB) step.

In comparison with the centralized VSBL algorithm, this algorithm allows each sensor to parallelly reconstruct sparse signal with local information and moderate inter-node communication.

Most recent developed Green Distributed signal reconstruction algorithm in WSN is shown below; IEEE Access 2016.on which it form the basis of this study.

1**:** Initialization: $S^{i}_{z,0|-1} = S_0, \hat{x}_{i,0|-1} = x_{0|-1}, j \in \mathcal{N}_i \cup \{i\}$.

2: Compute the square-root of the information contribution matrix $S_{\mathcal{T}_{i,k}[1]} = H^T_{i,k} S^{-1}_{R_{i,k}}$ of sensor node i and $U_{i,k} = S_{\mathcal{T}^{[1]}_{i,k}}$

3: Compute the information contribution vector and transmits it to the fusion centre; $t_{i,k} = H^T_{i,k} y_{i,k}\ of\ sensor\ node\ i$ and $u_{i,k} = t_{i,k}$

4: Independently perform average consensus on $u_{i,k} = u_i$

5: For $\mathcal{T} = 1, \dots \dots, T_{\mathcal{T}}$ **do**

6: Send message $msg_i\{u_{i,k,} U_{i,k}\}$ to neighbor nodes

7: update:

$$u_i(\mathcal{T}+1) = u_i(\mathcal{T}) + \sum_{j=1}^{N}\left(u_j(\mathcal{T}) - u_i(\mathcal{T})\right)$$

$$U_i(\mathcal{T}+1) = U_{i(\mathcal{T})} + \sum_{j=1}^{N}\left(U_{j^{(\mathcal{T})}} - U_{i^{(\mathcal{T})}}\right)$$

9: end for

$$\hat{t}_k = u_{i,k}$$

$$\hat{S}_{\mathcal{T}_k^{[1]}} = U_{i,k}$$

10: Compute the local measurement update using

$$\hat{S}_{z,k|k}^{-} = \left[qr\left(\left[\hat{S}_{z,k|k-1}^{1}\hat{S}_{\mathcal{T}_k^{[1]}}\right]^T\right)\right]^T$$

$$\hat{x}_{i,k|k}^{-} = \hat{x}_{x,k|k-1}$$

$$+\left(\hat{S}_{z,k|k}^{i}\right)^{-T}\left(\hat{S}_{z,k|k}^{i}\right)^{-1}\left(\hat{t}_k - \hat{S}_{\mathcal{T}_k^{[1]}\hat{x}_{i,k|k-1}}\right)$$

11: Compute the local pseudo-measurement update using

$S_{z,k|k}^{i} = \left[qr\left(\left[\left(\hat{S}_{z,k|k}^{i}\bar{S}_{\mathcal{T}_{i,k}^{[2]}}\right)\right]^T\right)\right]^T$ Minus

$$\hat{x}_{i,k|k} = \left(I_n - \left(S_{z,k|k}^{i}\right)^{-T}\left(S_{z,k|k}^{i}\right)^{-1}\bar{S}_{\mathcal{T}_{i,k}^{2}}\bar{S}_{\mathcal{T}_{i,k}^{[2]}}^{T}\right)\hat{x}_{i,k|k}^{-}$$

12: Compute the time update using $x_{j,k|k}^{i} = \left(S_{z,k|k}^{i}\right)^{-T\xi j+\hat{x}_{i,k|k}}$

Minus $\gamma_{k+1|k}^{i*} = \frac{1}{\sqrt{2n}}\left[\chi_{1,k+1|k}^{i*} - \hat{x}_{l,k+1|k,}x_{2,k+1|k}^{i*} - \hat{x}_{l,k+1|k} \dots \dots \dots, x_{2n,k+1|k}^{i*} - \hat{x}_{i,k+1|k}\right]$

2.7.5 Signal Fusion and Data Communication Protocols

Signal fusion can play a supporting role or a leading role. In the former, we have Signal fusion acting as a tool to assist the communication protocol establishment, whereas in the latter, the communication protocols are designed to support an signal fusion application (e.g., data aggregation target tracking).

Information fusion is a promising tool to support different tasks in WSNs MAC protocols has used information fusion techniques intensively. Fuzzy logic is used by Wallace et al. [2005]

and Liang and Ren [2005b] to define nodes' duty cycle in the MAC layer. Wallace et al. [2005] propose a fuzzy-based approach that- based on nodes' transmit-queue size, residual energy, and collision rate-defines the nodes' duty cycle so that nodes with high transmit queue have priority to access the medium. Moving average filters have been used by MAC protocols with different purposes such as: estimating ambient noise to determine whether the channel is clear [Polastre et al.2004]; local clock synchronization for contention purposes [Rhee et al. 2005]; and ACM Computing Surveys, Vol. 39, No. 3, Article 9, Publication date: August 2007. Article 9 / 40 *E. F. Nakamura et al.* detecting incipient congestion for fair and efficient rate control [Rangwala et al. 2006]. Kalman filters have been used to predict the frame size, avoiding the transmission of large frames whenever possible [Ci et al. 2004; Raviraj et al. 2005; Ci and Sharif 2005]. We can also point out some routing solutions that use information fusion searching for improved performance. Fuzzy logic has been used to decide the nodes participating in the routing path [Liang and Ren 2005a; Srinivasan et al. 2006]. In order to improve the network lifetime, Liang and Ren [2005a] use fuzzy logic to evaluate different parameters- such as battery capacity, mobility, and distance to the destination - and choose the nodes to be included in the routing path. Woo et al. [2003] use moving average filters within adaptive link estimators so that link connectivity statistics are exploited by routing protocols to reduce packet losses. Nakamura et al. [2005b] use the moving average filter to estimate the data traffic of continuous WSNs, and that estimate is further used to detect routing failure by means of the Dempster-Shafer inference. The SCAR algorithm [Mascolo and Musolesi 2006] uses the Kalman filter to predict context information (mobility and resources) about its neighbors, and choose the best neighbor for routing its data. Hartl and Li [2004] use maximum likelihood to estimate per-node loss rates during the aggregation and reporting of data from sources to sink nodes, which can be used to bypass lossy areas. Localized algorithms, wherein nodes make decisions based on neighbors' information (e.g., link quality, residual energy, connectivity, and mobility), can take advantage of dual prediction schemes to reduce communication. In this scheme, two neighbor nodes simultaneously apply a predictive estimator (e.g., the Kalman filter) so that a node only exchanges data when it knows its parameters are not being correctly predicted by its neighbor. Furthermore, besides using information fusion methods to estimate parameters, such as residual energy, inference techniques can also be used to make decisions. For instance, MAC protocols may use the Bayesian inference or neural networks to accurately decide whether or not it is worth trying to transmit data given the current link quality, resources, and QoS requirements. To determine whether or not the applicability of fusion methods in such situations is feasible, we must evaluate the computational cost of the fusion algorithms, the resultant delay, the energy consumed, and the impact on the quality of the service provided by communication protocol. Information Fusion for Wireless Sensor Networks Article 9 / 41 in data aggregation applications, a sink node is interested in collecting aggregated data from a subset of nodes. In this context, data communication should use as few nodes and resources as possible to ensure the delivery and aggregation of data generated by source nodes. This is essentially an NP-complete problem similar to the Steiner tree; some heuristics have been proposed for that problem. Three heuristics are evaluated by Krishnamachari et al. [2002]: the centered-at-nearest-source tree (CNS), the shortest-path tree (SPT), and the greedy incremental tree (GIT). In the CNS, each source sends its data directly to the source closest to the sink; in the SPT, each source sends its data to the sink along the shortest path between both nodes; and in the GIT, the routing tree starts with the shortest path between the sink and the nearest source, and at each step after that, the source closest to the current tree is included in the tree. As Krishnamachari et al. [2002] show, the GIT heuristic is the best of the three. However, its distributed version [Bauer and Varma 1996] demands a lot of communication and memory usage, because every node needs to know its shortest paths to the other nodes in the network. Motivated by that infeasible cost, Nakamura et al. [2006] propose the InFRA heuristic, which finds the shortest paths that maximize data aggregation, and has an $O(1)$-approximation ratio. Zhu et al. [2005] present a heuristic, called Semantic/ Spatial Correlation-aware Tree (SCT), that is constructed during the course of a query delivery. The SCT builds a fixed aggregation backbone that simplifies the generation of efficient aggregation trees, and is independent of source distribution and density. However, in contrast to the InFRA heuristics [Nakamura et al. 2006], the SCT needs to be pro-actively rebuilt, leading to energy waste. For the same problem, Ding et al. [2003] propose a tree-based routing algorithm based on nodes' residual energy, so that nodes with more energy are likely to perform data aggregation and routing. Once the tree is built, leaf nodes are turned off to save energy, but no approximation ratio is provided for this heuristic. Another approach to the aforementioned problem is the use of role assignment algorithms to define which nodes are to be used and what actions those nodes should take. Bhardwaj and Chandakasan [2002] derive upper bounds on the lifetime of WSNs that perform information fusion by assigning roles (sensor, relay, and aggregator), and modeling the optimal role assignment as a linear problem to find the assignment that maximizes the network lifetime. By computing a user-defined cost function, Bonfils and Bonnet [2003] propose an adaptive and decentralized solution that progressively refines the role assignment. The SPRING algorithm [Dasgupta et al. 2003] for mobile sensor networks defines two roles (sensor and relay/aggregator), and places nodes and assigns roles to them so the system's lifetime is maximized and the region of interest is covered by at least one sensor node. In the DFuse framework [Kumar et al. 2003], role assignment is provided by a heuristic in which a tree with a naive role assignment is created, then nodes exchange health information, and the role is transferred to the neighbor with the best health regarding a given cost function. Frank and R¨omer [2005] propose a basic structure for a generic role assignment framework with applications for coverage, clustering, and in-network aggregation. Similarly to the filter approach of Directed Diffusion, the network designer should specify roles and assignment rules. When we have information fusion as a leading role, source selection and route selections are problems of major concern. Taking target tracking applications based on particle filters as an example, selecting good particles (samples) for estimating a target's trajectory is challenging because the fewer particles the cheaper the computation. In this context, Zhao et al. [2002a; 2003a] propose an information-directed approach in which sources and communicating nodes are chosen by dynamically optimizing the information utility of data for a given cost of communication and computation. Chen et al. [2006c] propose the Energy-Efficient Protocol for Aggregator Selection (EPAS) for selecting nodes that perform information fusion. The authors derive the ACM Computing Surveys, Vol. 39, No. 3, Article 9, Publication date: August 2007. Article 9 / 42 E. F. Nakamura et al. optimal number of aggregators, and present fully distributed algorithms for the aggregator selection. A key contribution is that these algorithms are independent of routing protocols. Chen et al. [2006b] use a cluster-based communication architecture, based on LEACH [Heinzelman et al. 2000], wherein data aggregation runs parallel to the cluster-heads, improving the energy efficiency via Meta data negotiation. In addition, for each event and each cluster, only one of the cluster members is selected to send data to the cluster-head. Zhou et al. [2004] use Directed Diffusion to provide a hierarchical aggregation scheme for WSNs to improve reliability and provide more applicable data aggregation.

2.8. CONCEPTUNAL FRAMEWORK.

The sensor node is largely deployed within or near the monitored area through artificial arrangement as shown in the figure 2.8.1. each sensor node are statically and randomly distributed in particular area Data through a simple processing jumping to transfer between neighboring nodes, monitoring data can be processed by multiple test nodes during transmission, to arrive at sink nodes after multiple hops posterior. Sink nodes transfer a network through transmission network, and finally transfer a collected data to a remote information processing center. Fig I below is the sensor network structure, which includes sensor nodes, sink nodes and information processing centre, etc

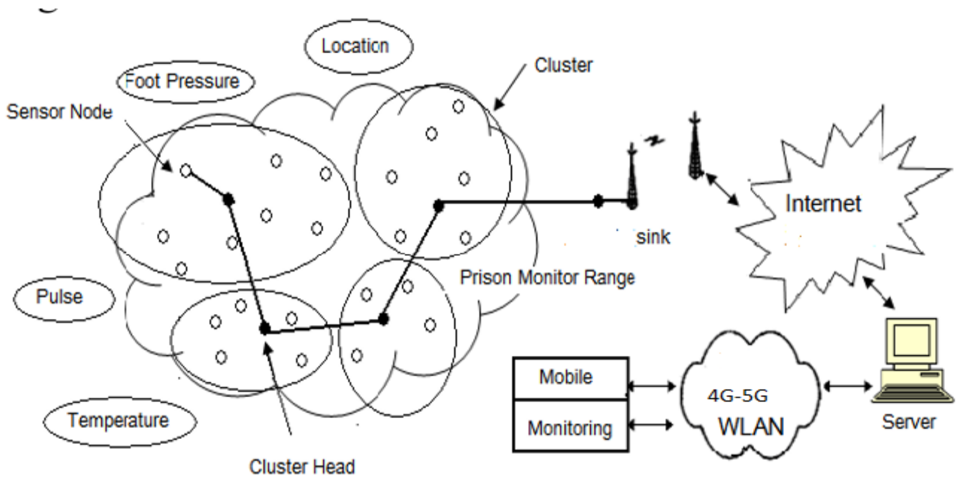

Fig 2:8:1. Framework of WSN

Consider a network employing the sensors which observe linear combination of sparse state from a general nonlinear dynamical system described from equation;

$$x_{k+1} = f(x_k) + v_k \tag{4:1}$$

$$y_k = H_k x_k + w_k \tag{4:2}$$

Here, x_k denotes a time varying state vector which is sparse in some transform domain, i.e. $x_k = \Psi s_k$ where the majority of the components of s_k are zero and Ψ is an appropriate basis. Without a loss of generality, it has been assumed that x_k itself is sparse, having at most K nonzero components with unknown locations $(K \ll N)$.at time k, the observation at sensor i is$y_{i,k} = H_{i,k} x_k + w_{i,k}$Where $H_{i,k} \in R^{pi \times n}$ is the local observation matrix for sensor i,p_i is the number of simultaneous observation made by sensor i at time k, and $w_{i,k} \epsilon R^{pi}$ is the observation noise.

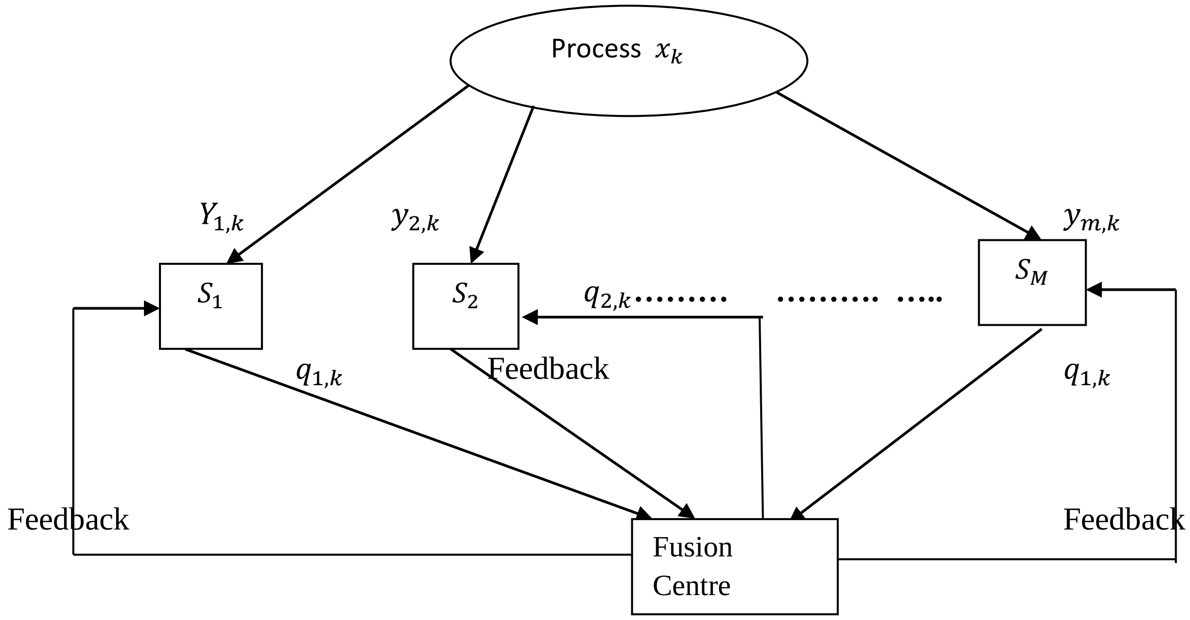

Figure 2:8:2.Conceptual framework

The goal of the WSN is to form an estimate of sparse signal x_k at the fusion centre. Due to energy and bandwidth constrains, the observed analog measurements needs to be quantized/coded before sending them to the fusion center. Moreover, the quantized innovation scheme also can be used. At time k, the l_{th} sensor observes a measurement $y_{l,k}$ and computes the innovation$e_{l,k} = y_{l,k} - h_l\hat{X}_{k|k-1}$, where $h_l\hat{X}_{k|k-1}$ together with the variance of innovation $Cov[e_{l,k}]$ is received from the fusion center. Then; the innovation $e_{l,k}$ is quantized to $q_{1,k}$ and sent to fusion center. As the fusion center has enough energy and enough transmission bandwidth, the data transmitted by the fusion center do not to be quantized. The decision of which sensor is active at time k and consequently which observation innovation $e_{l,k}$ gets transmitted depends on the scheduling algorithm. The quantized transmission of $e_{l,k}$ also implies that $q_{1,k}$ can be viewed as a nonlinear function of the sensor's analog observation. As shown in the above conceptual framework.

CHAPTER THREE

METHODOLOGY

3.0. INTRODUCTION

This chapter comprises of research design, research Instrument, Validity and reliability of the instrument, Data collection procedure and Data processing and analysis.

3.1. RESEARCH DESIGN

3.1.1. Bayesian Estimation and Kalman filters.

We provide a self-contained derivation of Bayesian estimation results leading to the Kalman filter with emphasis on conceptual simplicity to solve non-linear problem in a distributed WSNs. The problem of interests concerns the estimation of an observed discrete-time random signal in a dynamic system (state of the system) State equation model the evolution in time of state as a discrete-time stochastic function. In general;

$$x_k = Y_{k-1}(x_{t-1}, S_m)$$

Y_{k-1} is known possibly nonlinear. A function of the state x_k and S_m is referred to as Process noise which filter any mismodelling effect on distribution in the state characterization.

The relation between measurement and the state is modeled by;

$$S_t = q_k(x_t, n_t)$$

Both process and measurements noise are assumed with known statistics and mutually independent. The filtering problem involved in the Bayesian estimation can be solved analytically.

3.1.2. Experimental Results.

Experiment setting.

Through simulation of a wireless sensor network Algorithm to demonstrate the performance of the algorithm for distributed WSNs, A sensor network with 6 nodes is considered without the loss of generality. The network is represented by an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ with sets of nodes $\mathcal{A} = (1,2,3,4,5,6)$,the set of edges $\mathcal{E} =$

$\{(1,1),(1,2),(1,3),(2,3),(2,4)(2,5),(3,3),(3,5),(3,6)(4,4),(4,5),(5,5),(5,6),(6,6)\}$, and the adjacency.

3.2. TARGET POPULATIONS

3:1:1.Expert Opinion

Collection of data is by expert opinion. This non-probabilistic exercise where opinion are gathered. “Expert knowledge” is what qualified individuals know as a result of their technical practices, training, and experience (Booker and McNamara 2004). It may include recalled facts or evidence, inferences made by the expert on the basis of “hard facts” in response to new or undocumented situations, and integration of disparate sources in conceptual models to address system-level issues (Kaplan 1992) .Experts are usually identified on the basis of qualifications, training, experience, professional memberships, and peer recognition (Ayyub 2001) .1

Bogner and Menz (formulate this as follows: “An expert has technical, process and interpretative knowledge that refers to a specific field of action, by virtue of the fact that the expert acts in a relevant way (for example, in a particular organizational field or the expert’s own professional area). In this respect, expert knowledge consists not only of systematized, reflexively accessible knowledge relating to a specialized subject or field, but also has to a considerable extent the character of practical or action knowledge, which incorporates a range of quite disparate maxims for action, individual rules of decision, collective orientations, and patterns of social interpretation. An expert’s knowledge, his/her action orientations etc., also (and this is decisive) point to the fact that s/he may become hegemonic in terms of practice in his/her field of action (for example, in a certain organizational functional context). In other words, the possibility exists that the expert may be able to get his/her orientations enforced (at least in part). As the expert’s knowledge has an effect on practice, it structures the conditions of action of other actors in the expert's field in a relevant way."

3:2:2.Selection of Experts

The selection process involves identification of the expertise that will be relevant to the elicitation process, and selection of the subset of experts who best fulfill the requirements for expertise within the existing time and resource constraints. In some cases, the selection of appropriate experts is straightforward, but in other cases, an appropriate expert group will need to be defined by the researcher according to the experts' availability and the requirements of the elicitation. I considered explicit criteria to ensure transparency, and to establish that the results represent the full range of views in the expert community. Common metrics for identifying experts include qualifications, employment, memberships in professional bodies, publication records, years of experience, peer nomination, and perceived standing in the expert community which core consideration during this process(e.g., Chuenpagdee et al. 2003 ; Drescher et al. 2008 ; Whitfield et al. 2008 ; Czembor and Vesk 2009) . Additional considerations include the availability and willingness of the experts to participate, and the possibility of conflicts of interest.

The appropriate number of experts depends on the scope of the problem, the available time and other resources, and the level of independence between experts. Experts often share beliefs because of shared information sources and training. In such cases, the marginal benefits of including more than about five to eight experts decrease quickly (Winkler and Makridakis 1983; Clemen and Winkler 1985). As a result, I included a diverse a range of experts as possible. I will contact multiple experts to buffer against individual mistakes and biases, and to allow for assessments that are representative of the whole expert community (Hokstad et al. 1998; Clemen and Winkler 1999; Armstrong 2006).

3:3.SAMPLING AND SAMPLING PROCEDURE

Literature on both forms of interview, that is interviews with the elite and interviews with experts often focuses on the issues of sampling, the specific access problems faced and the challenges of conducting the interviews for example (Dexter, 2006/1969, Moyser and Wagstaffe, 1987, Vogel, 1995, Odendahl and Shaw, 2002, Welch and others, 2002, Lilleker, 2003 and the articles in Bogner and others, 2005).

3:3:1.Sampling

Sampling does not adhere to quantitative conceptions of representativeness, since there is no clearly defined pool of experts and members of the elite from which a sample might be chosen in line with specific guidelines. Indeed, the attributed expert or elite status is more often set by the actual field of research and research goals. As Meuser and Nagel (2005, p. 73) note, researchers to a certain extent attribute expert status that is limited to a specific area of research. Welch (and others, 2002, p. 613) also describe the attribution of elite status to certain individuals in a similar manner, namely in relation to the research questions

3.4. RESEARCH INSTRUMENTS

3:3:1.Expert interview

Data were obtained from self administered expert opinion, there is no iron-clad rule about how many experts are enough however it is important to conduct as many as possible depending on the topics of interest that are relevant to answering of the research questions. See the table 4:2:1.below.

	Expert Name/Contacts	Field of expertise	Place of Interview/time & Date	Subject.
1.	Gilbert B.Mugeni,Ph.D gmugeni@yahoo.co.uk	Manager, Data management & Documentation Frequency Spectrum Management	CAK offices, Waiyaki way. 19th ,Sept.2017	Spectrum Management and WSN
2.	Eran Hadad ehadad@mmm.com	3M Electronic Monitoring ltd 3M Traffic, safety & Security Division	Tel Aviv 6583 office, Israel(Telephone conversation) 25th ,Sept.2017	Wireless Sensor Monitoring
3.	Dr.Feben Gobena ftgobena@mmm.com	3M AFRICA. General manager Government Affairs and Market	Victoria Tower, Victoria Tower, Upper Hill office 26th ,Sept.2017	Security Surveillance in African Penal Institution & policy issues
4.	Guy Johananoff gjohananoff.cw@mmm.com	3M Electronic Monitoring ltd 3M Traffic, safety & Security Manager.	2 Habarzel st,6489 Office Serena Hotel, 26th ,Sept.2017	WSN ,IoT and Energy
5.	Andrew Ngugi www.axis.com	Axis Communication Kenya. Engineer	Delta corner Tower westlands 7th floor office 709 29th ,Sept.2017	Intelligent system Surveillance
6.	Mr. J.M.kodieny ,OGW (SDCP)	Dir.Operation Prisons	Prisons Headquarters Magreza Hse, Bishop Road.	Prisons Security. and Technology
7.	Emanuel Mugo emugo@gmail.com	Kenya Prisons ICT Manager	Prisons Headquarters Magreza Hse,Bishop Road	ICT infrastructure
8.	Mr. Wamyama wamyamadw@gmail.com	Former Chief Telecommunication Engineer Prisons Hqs.	Kengele's Restaurant westlands. 29th ,Sept.2017	Wireless Communication infrastructure

Table 4:1:1.Table of Experts

N/B. The Interactive Interview (through expert opinion) is based on the assumption that the discussion with the respondents (researcher) is a learning process that continues throughout the field work. Daily interpretive analysis (DIA) was itself a potentially valuable learning tool because it forced me to reflect on what has been learned. Such reflections positively informed subsequent interviews that we carried out.

The explication and reconstruction of these different forms of knowledge and their practical consequences form the focus of expert interviews and their subsequent analysis (cf. the articles in Bogner and others, 2005).

3.5. VALIDITY AND RELIABILITY OF THE INSTRUMENT.

3.4.1. Validity and Reliability

Indeed, issues of validity and reliability of research instruments are of great of great significance to the findings of any scientific research. Moreover, as Dornyei (2007) adds, validity and reliability issues serve as guarantees of the results of the participants' performances. In its broader context, validity refers to the degree to which a study reflect the specific concepts it aims to investigate. Two types of validity are discussed in social science literature: internal and external (Berg, 2007). Internal validity refers to the extent to which an investigation is actually measuring what it is supposed to measure. This type of validity answers the question: Are the differences found related to the measurement? While external validity answers the question: Can the findings be generalized? Yet, in order to maintain this, researchers should consider a number of factors. Cohen et al (2007) propose the following factors which may lead to higher validity by minimizing the possibility of bias:

a) The attitude, views and prospects of the interviewer;
b) A tendency for interviewer to see the interviewee on his/her own merits;
c) A tendency for interviewers to seek answers to support their preconceived notions;
d) Misperceptions on the part of the interviewer with regard to what the interviewee is saying; and
e) Misunderstanding on the part of the interviewee with regard to what is being asked.

On the other hand, reliability refers to the extent to which a research instrument yields the same results on repeated trials. Yet, Brewerton and Millward (2001) justifiably argue that interviews have poor reliability: "…due to their openness to so many types of bias, interviews can be notoriously unreliable, particularly when the researcher wishes to draw comparisons between data sets”. In line with this, Creswell (2009 :) claims that interviewing reliability is ‘elusive’ and he even adds that “no study reports actual reliability data”. In sum, researchers should follow techniques that would help maintaining the validity and reliability of interviewing. These can be:

a) Avoiding asking leading questions
b) Taking notes not just depending on tape recorders
c) Conducting a pilot interview; and giving the interviewee a chance to sum up and clarify the points they have made.
d) Experts are asked to review their judgments, consider alternatives, and verify or change their judgments if they wish. Experts are given an opportunity to review the outputs of any model or final representation, such as a graphical representation of the probability distribution constructed from their responses, to ensure that this result represents a reasonable reflection of their beliefs. Actively questioned the expert, and provided examples of their responses in multiple formats to prompt the expert to reconsider their statements in a new light.

3.6. DATA PROCESSING AND ANALYSIS.

3.6.1. Mathematical Induction

We use mathematical induction mainly a tool for explaining and designing algorithm. This has been done by many researchers and scholars’ including (Dijikastra 1976), (Manna 1980), (Gries 1981) (Dershows 1983) and (Paul 1988) among many others. The significance of the approach is to first collect seemingly different technique of algorithm design into one umbrella and second to utilize known mathematical proof technique for algorithm design.

CHAPTER FOUR

EXPRIMENTATIONS, FINDING AND DISCUSSION

4.0. Introduction.

This chapter presents the systematic look of the research questions, analysis of the result of experimentation followed by a discussion of the research findings.

4.1. DISTRIBUTED NONLINEAR STATE ESTIMATION PROBLEMS IN WSNS.

Algorithms for WSNs are investigated in the literature review, Therefore in this section we investigate distributed non linear state estimation problem in WSNs and there solutions.

4.1.1. The problem statement

Given a nonlinear dynamic system, estimate the hidden state of the system in a recursive manner by processing a sequence of noisy observations dependent on the state. The Bayesian filter provides a unifying framework for the optimal solution of this problem, at least in a conceptual sense.

1. System (state) Model

$X_{t+1} = a(X_t) + \omega_t$ (Refer to eqn 4:1Conceptual framework)

2. Measurement model

$y_t = b(X_t) + v_t$ (Refer to eqn 4:2 Conceptual framework)

Where $t =$ discrete time

$X_t =$ State at time t

$y_t =$ Observation at time t

$\omega =$ Dynamic noise

$v_t =$ Measurement

Assumption:

- Nonlinear function a (·) and b (·) are known

- Dynamic noise ω_t and measurement noise v_t are statistically independent Gaussian processes of zero mean and known covariance matrices.

1. Time-update equation:

$$P(X_t|Y_{t-1}) = \int_{R^n} P(X_t|X_{t-1})P(X_{t-1}|Y_{t-1})dX_{t-1}$$

$P(X_t|Y_{t-1})$ - Predictive distribution.

$\int_{R^n} P(X_t|X_{t-1})$ - Prior distribution.

$P(X_{t-1}|Y_{t-1})dX_{t-1}$ - Old posterior distribution.

Where R^n denotes the n- dimensional state space.

2. Measurement-update equation:

$$P(X_t|Y_t) = \frac{1}{Z_t} P(X_t|Y_{t-1})l(y_t|X_t)$$

$P(X_t|Y_t)$ - Updated posterior distribution.

$P(X_t|Y_{t-1})$ - Predictive distribution.

$l(y_t|X_t)$ - Likelihood function.

Where Z_t is the normalizing constant defined by,

$$Z_t = \int_{R^n} P(X_t|Y_{t-1})l(Y_t|X_t)dX_t$$

The celebrated Kalman filters is a special is a special case of the Bayesian filter, assuming that the dynamics system is linear and both the dynamic noise and measurement noise are statistically independently processes.

Except for this special case and couple of other cases, exact computation of the predictive distribution $P(X_t|Y_{t-1})$ is not feasible.

We therefore have to abandon optimality and be content with a sub-optimal nonlinear filtering algorithm that is computationally tractable.

Nonlinear problem geometries often assume that the measurements are related to the state using the nonlinear relation $Z_n = h_n(X_n) + N_n$.(Refer conceptual framework egn 4:2) With this non linear form of the measurement model employed, the current optimal estimate can only approximately be represented as a linear combination of the measurement. The usual procedure is either to iterate the solution until acceptable accuracy is obtained or simply ignore the partial derivatives of $h_n(X_n)$ that is higher than the first.

A new approach to nonlinear filtering with correlated measurement noise is presented on this research. This approach, using pseudo state measurements, differs from the usual approach of the extended Kalman filter. The latter approach requires the computation of nonlinear residuals and uses nonlinear propagation of the state. The approach defined in this study uses a nonlinear transformation of the actual measurements and the a priori state variables to obtain pseudo state measurements.

Roots embedded in Monte Carlo simulation computationally demanding the Cubature Kalman Filter which is the basis for nonlinear solution in this study. At the heart of the Bayesian filter, we have to compute integral whose integrands are expressed in the common form.

(Nonlinear function) X (Gaussian function)

The challenge is to numerically approximate the integral so as to completely preserve second-order information about the state X_t that is contained in the sequence of observations Y_t

The computational tool that accommodates this requirement is the cubature rule. In mathematical terms, we have to compute an integral of the generic form.

$$h(f) = \int_{R^n} f(X) exp\left(-\frac{1}{2}X^T X\right) dX$$

$f(X)$ Arbitrary nonlinear function.

$exp\left(-\frac{1}{2}X^T X\right)$ Normalized Gaussian functions of zero mean and unit covariance matrix.

To do the computation, a key step is to make a change of variable from the Cartesian coordinate system (in which the vector x is defined) to a spherical radial coordinate system:

$X = rZ$ Subject to $Z^T Z = 1$ and $X^T X = r^2$ where $0 \leq Z < \infty$

The next step is to apply the radial rule using the Gaussian quadrature.

The pseudo-measurement equation is interpreted from the Bayesian perspective, and semi-Gaussian prior distribution discussed

For the system given in eq. (4:1) and eq. (4:2), it is well-known that Kalman filtering can provide an estimation of x_k which is equivalent to the solution of the following unconstrained ℓ_2 minimization problem.

$$\min_{\hat{x}_k \in R^n} E_{xk} \, |y_1 \cdots , y_k [\|x_k - \hat{x}_k\|_2^2 \quad]| \qquad (4:8)$$

Where;

$E_{xk|y_1,\cdots,y_k|}[\cdot]$ is the conditional expectation of the given measurements? $\{y_1, \cdots , y_k\}$

Consider the following stochastic case;

$$\min_{\hat{x}_k \in R^n} \|\hat{x}_k\|_{1,} s, t. \, x_{xk|y_1,\cdots,y_k|} [\|x_k - \hat{x}_k\|_2^2 \quad] \leq \in \qquad (4:9)$$

And its dual problem are discussed in the KF framework

$$\min_{\hat{x}_k \in R^n} E_{xk|y_1,\cdots,y_k|} \, [\|x_k, \cdots , \hat{x}_k\|_2^2 \quad], \|\hat{x}_k\|_1 \leq \in \qquad (5:0)$$

The constrained optimization problem is solved in the framework of Kalman filtering and the specific method summarized as a CS-embedded KF with ℓ_1-norm constraint (CSKF).

The CSKF is generalized and applied to nonlinear systems. In particular, a cubature Kalman filter is employed in place of the Kalman filter and the resulting algorithm is implemented in centralized manner.

For a general nonlinear dynamical system, it is to abandon the optimal solution stated in the problem and to content with a suboptimal solution to Bayesian filter by using approximate methods. In case of compressive sensing applications, the state-space models are high-dimensional with state-space models are high-dimensional with state-vector of size hundreds or more.However,the general nonlinear filter suffer from the curse of dimensionality.Fortunately,the CKF is recently developed for closest approximation to Bayesian filter and can be applied to solve high-dimensional nonlinear problems. Under the

Gaussians assumption, the multi-dimensional integral of the Bayesian filters solution are of the form

$$I(f) = \int_{R^n} f(x)\, exp(-x^T x) dx \tag{5:7}$$

However, this multi-dimensional integral is typically intractable. The third degree spherical radial cubature rule is used to approximate the integral. This rule is used to approximate the integral. This rule uses the spherical radial transformation to change the variables from the Cartesian to the radial as:$x = rz$ z with $z^T z = 1$,such that $x^T x = r^2$ for $r \in [0, \infty)$.The integral equation (a) is then numerically approximated by

$$I(f) \approx \frac{\sqrt{\pi^n}}{2n} \sum_{j=1}^{2n} f\left(\sqrt{\frac{n}{2}}\ \xi_j\right) \tag{5:8}$$

Where n is the dimensions of the vector x, and ξ_j is the j-th cubature point located at the intersection of the surface of the surface of n-dimensional unit sphere and its axes. This rule can be extended to solve the prediction and posterior pdfs that are in the form of standard Gaussian with mean $\hat{x}$ and the variance $\boldsymbol{P}$. Hence, the cubature rule to approximate an n-dimensioning Gaussian-weighted integral is as follows

$$\int_{R^n} f(x) \mathcal{N}(x; \hat{x}, P) dx \approx \frac{1}{2n} \sum_{j=1}^{2n} f\left(\hat{x} + S_x \xi_j\right) \tag{5:9}$$

Where S_x is a square-root factor of the covariance P satisfying the relation $\square = \square_{\square} \square_{\square}^{\square}$; $\square_{\square}$ is the j-th element of the cubature points set$\{\square_{\square}\}$

In particular, the system has an underlying state-space structure, where the state vector is sparse. in each time interval, the fusion center transmits the predicted signal estimate and its corresponding error covariance to a selected subset sensor. The selected sensors compute quantized innovation and transmit them to the fusion center. The fusion centre reconstructs the sparse state by employing the filter algorithm and sparse cubature point method.

4.2. WSN SIGNAL RECONSTRUCTION ALGORITHM

In this section Distributed square root cubature information filtering with pseudo measurement embedded and Signal fusion center algorithms is developed for sparse estimation. It is worth noting that a fusion center is required to implement the state estimate and sparse constraint, when observations are distributed among the sensors. This is unique from the algorithm discussed in the literature review and forms the basis of this algorithm.

This difference makes the information filter superior to the Kalman filter because no a priori about the system state is required. Moreover, the information filter can be easily decentralized and extended to multi-sensor fusion.

ALGORITHM

1**:** Initialization: $□^{□}_{□,0|-1} = □_{0}, \hat{□}_{□,0|-1} = □_{0|-1}, □ \in □_{□} \cup \{□\}$.

2: Compute the square-root of the information contribution matrix $□_{□_{□,□}[1]} = □^{□}_{□,□} □^{-1}_{□_{□,□}}$ of sensor node *i* and $□_{□,□} = □_{□^{[1]}_{□,□}}$

3: The fusion centre transmits $□_{□_{□}}(□,□)$ which denotes the $(□,□)$ entry of the innovation error covariance matrix and predicted observation $\hat{□}_{□,□}$ to the $□□h$ sensor

$$□^{□□}_{1|1} = □_{□|□}, \hat{□}_{1|1} = \hat{□}_{□|□}.$$

$$□^{□□}_{□} = \left[□□□□\left(\hat{□}_{1,□|□}\right) \ldots .□□□□\left(\hat{□}_{□,□|□}\right)\right]$$

$$□^{□□} = \frac{□^{□□}_{□|□} □^{□□}_{□}}{□^{□□}_{□} □^{□□}_{□|□} (□^{□□}_{□})^{□} + □_{□}}$$

$$\hat{□}_{□+1|□+1} = \hat{□}_{□|□} - □^{□□} □^{□□}_{□} \hat{□}_{□|□}$$

$$□^{□□}_{□+1|□+1} = □^{□□}_{□|□} - □^{□□} □^{□□}_{□} □^{□□}_{□|□}$$

$$\hat{□}_{□|□} = \hat{□}_{□|□}, □_{□|□} = □^{□□}_{□+1|□+1}$$

4: The $□□□$ sensor Compute the information contribution vector and transmits it to the fusion centre; $□_{□,□} = □^{□}_{□,□} □_{□,□}$ □□ □□□□□□ □□□□ □ and $□_{□,□} = □_{□,□}$

4: Independently perform average consensus on $□_{□,□} = □_{□}$

5: For $\square = 1, \ldots\ldots, \square_{\square}\ \square\square$

6: Send message $\square\square\square_{\square}\{\square_{\square,\square}, \square_{\square,\square}\}$ to neighbor nodes

7: update:

$$\square_{\square}(\square + 1) = \square_{\square}(\square) + \sum_{\square=1}^{\square}\left(\square_{\square}(\square) - \square_{\square}(\square)\right)$$

$$\square_{\square}(\square + 1) = \square_{\square(\square)} + \sum_{\square=1}^{\square}\left(\square_{\square(\mathcal{T})} - \square_{\square(\square)}\right)$$

9: end for

$$\hat{\square}_{\square} = \square_{\square,\square}$$

$$\hat{\square}_{\square_{\square}^{[1]}} = \square_{\square,\square}$$

10: Compute the local measurement update using

$$\hat{\square}^{-}_{\square,\square|\square} = \left[\square\square\left(\left[\hat{\square}^{1}_{\square,\square|\square-1}\hat{\square}_{\square_{\square}^{[1]}}\right]^{\square}\right)\right]^{\square}$$

$$\hat{\square}^{-}_{\square,\square|\square} = \hat{\square}_{\square,\square|\square-1}$$

$$+\left(\hat{\square}^{\square}_{\square,\square|\square}\right)^{-\square}\left(\hat{\square}^{\square}_{\square,\square|\square}\right)^{-1}\left(\hat{\square}_{\square} - \hat{\square}_{\square_{\square}^{[1]}\hat{\square}_{\square,\square|\square-1}}\right)$$

11: Compute the local pseudo-measurement update using

$$\square^{\square}_{\square,\square|\square} = \left[\square\square\left(\left[\left(\hat{\square}^{\square}_{\square,\square|\square}\bar{\square}_{\square_{\square,\square}^{[2]}}\right)\right]^{\square}\right)\right]^{\square}$$ Minus

$$\hat{\square}_{\square,\square|\square} = \left(\square_{\square} - \left(S^{\square}_{\square,\square|\square}\right)^{-\square}\left(\square^{\square}_{\square,\square|\square}\right)^{-1}\bar{\square}_{\square^{2}_{\square,\square}}\bar{\square}^{\square}_{\square_{\square,\square}^{[2]}}\right)\hat{\square}^{-}_{\square,\square|\square}$$

12: Compute the time update using $\square^{\square}_{\square,\square|\square} = \left(\square^{\square}_{\square,\square|\square}\right)^{-\square\square\square+\hat{\square}_{\square,\square|\square}}$

Minus $\square^{\square *}_{\square+1|\square} = \frac{1}{\sqrt{2\square}}\left[\square^{\square *}_{1,\square+1|\square} - \hat{\square}_{\square,\square+1|\square}, \square^{\square *}_{2,\square+1|\square} - \hat{\square}_{\square,\square+1|\square} \ldots\ldots\ldots, \square^{\square *}_{2\square,\square+1|\square} - \hat{\square}_{\square,\square+1|\square}\right]$

4.3. Comments

The information filter (IF) utilizes the information states and the inverse of covariance states and the inverse of covariance rather than the states and covariance, is the algebraically equivalent form of Kalman filters. The l_1-norm constraint is enforced in a distributed manner and the effectiveness enhanced by consensus update during the communication between the sensor nodes in the WSNs the derived square –root is lower triangular matrix using the QR decomposition. Therefore, the sparseness of square-root can reduce the storage space on sensor nodes and communication overhead in the WSN.

4:4. EXPERIMENT/SIMULATIONS:

In this section tests are performed using MATLab –morte Carlo simulation to test the performance of the algorithms in a fusion center based networks in which sparse signal are reconstructed from a series of a coarsely quantized observation.

MATLAB-morte Carlo simulation

To demonstrate the performance of the proposed algorithm for the distributed WSNs.A sensor network with 6 nodes is considered without the loss of generality. The network is represented by an undirected graph $\square = (\square, \square, \square)$ with the set of nodes $\square = (1,2,3,4,5,6)$, the set of edges $\square = \{(1,1), (1,2), (1,3), (2,3), (2,4), (2,5), (3,3), (3,5), (3,6), (4,4), (4,5), (5,5), (5,6), (6,6)\}$, and the adjacency.

In the following simulations the states are estimated using $\square = 200$ time steps from $\square = 50$ Monte- Carlo runs in Mat-lab.

The average of normalized RMSE is employed to evaluate the performance of the proposed algorithm, which is defined as follows.

$$\square\square\square\square\square\square(\square) = \frac{1}{\square}\sum_{\square=1}^{\square} \frac{\left\| \hat{\square}_{\square}^{\square} - \square_{\square}^{\square} \right\|_2}{\left\| \square_{\square}^{\square} \right\|_2} \tag{6:4}$$

Where $\square_{\square}^{\square}$ and $\hat{\square}_{\square}^{\square}$ is the true and estimated state variable at discrete time *k* of the j-th Morte Carlo run: and M is the number of morte Carlo runs. The expression describes the average convergence process of the filtering algorithm for all simulation. For convenience, the centralized SCIF-PM and the non square-root form of DSCIF-PM are referred as CSCIF-PM and DCIF respectively.

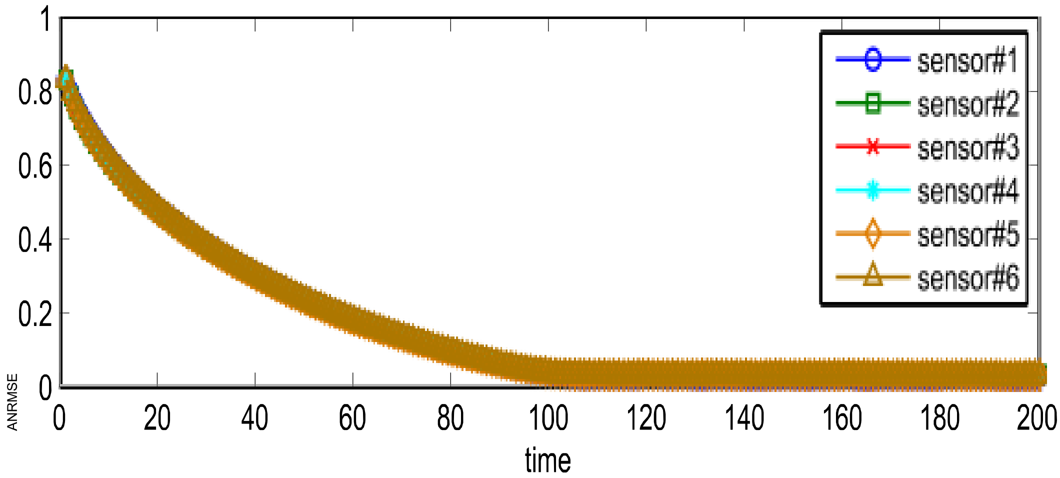

FIGURE.4.10.1. ANRMSE of DSCIF-PM

Fig 1.Presents the ANRMSE of all sensors indicating that all the local filters are stable and have reached an consensus on the estimate of the sparse signals.

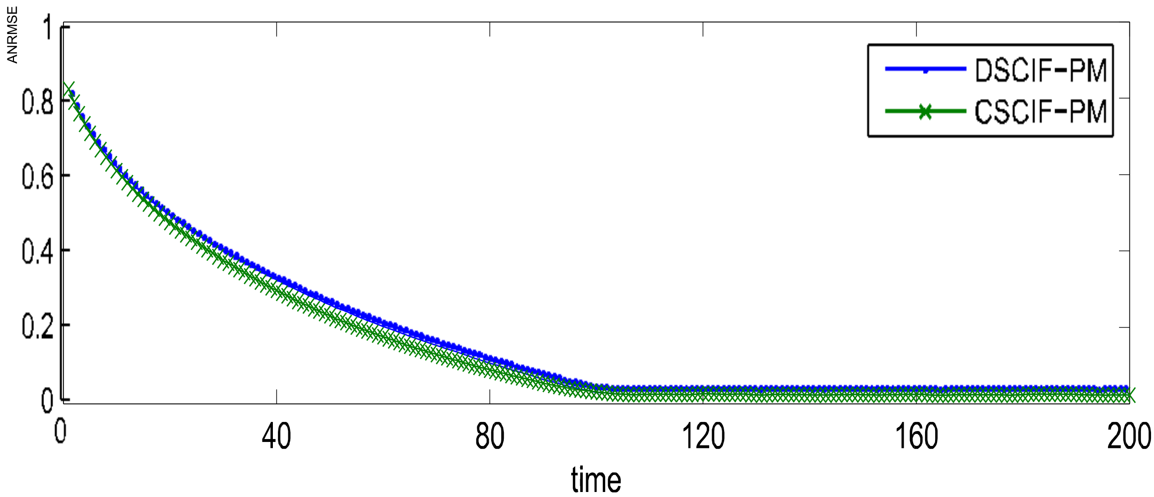

FIGURE 4.10.2. ANRMSE of CSCIF-PM and DSCIF-PM.

Fig 2 gives the state estimate from sensor nodes using the DSCIF-PM at time k = 200.Surely, all sensors nodes are providing satisfactory estimate of the true sparse signal.

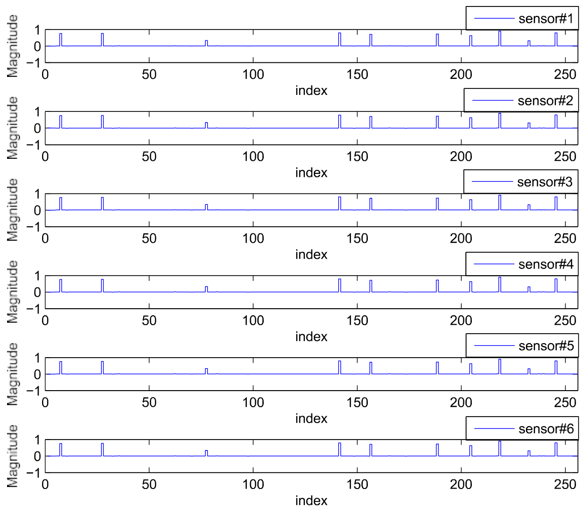

FIGURE 4:10:3. Estimation of x_{200} using DSCIF-PM.

The performance of the DSCIF-PM and the CSCIF-PM in ANRMSE is compared. In fig 3.it can be seen that DSCIF-PM is showing comparable performance to the CSCIF-PM.it means that the sparsity constraint in a distributed manner is effective.

Next, the performance of the DSCIF-PM and the DCIF-PM is compared

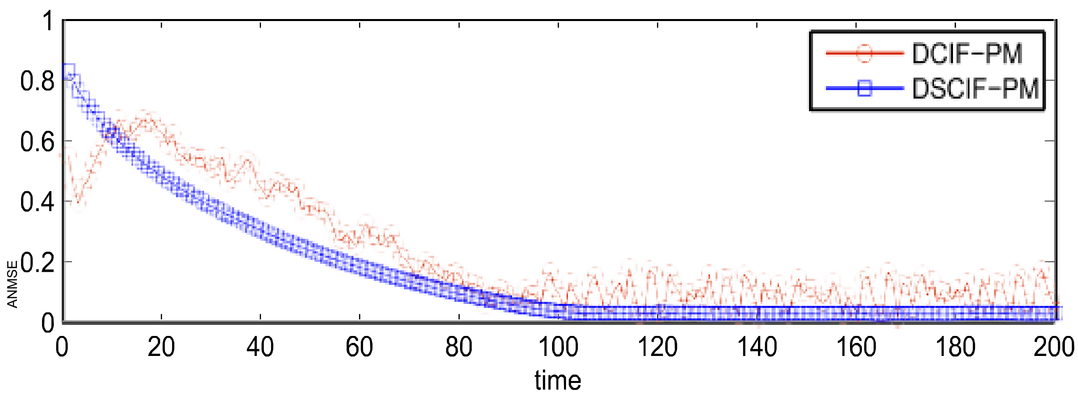

FIGURE 4.10.4. ANRMSE of DSCIF-PM and DCIF-PM.

Fig 4: 15:5.Shows, the ANRMSE of the DSCIF-PM and the DCIF-PM.Compared with DCIF-PM, the introduction of Square-root form has made the filter more stable and accurate.

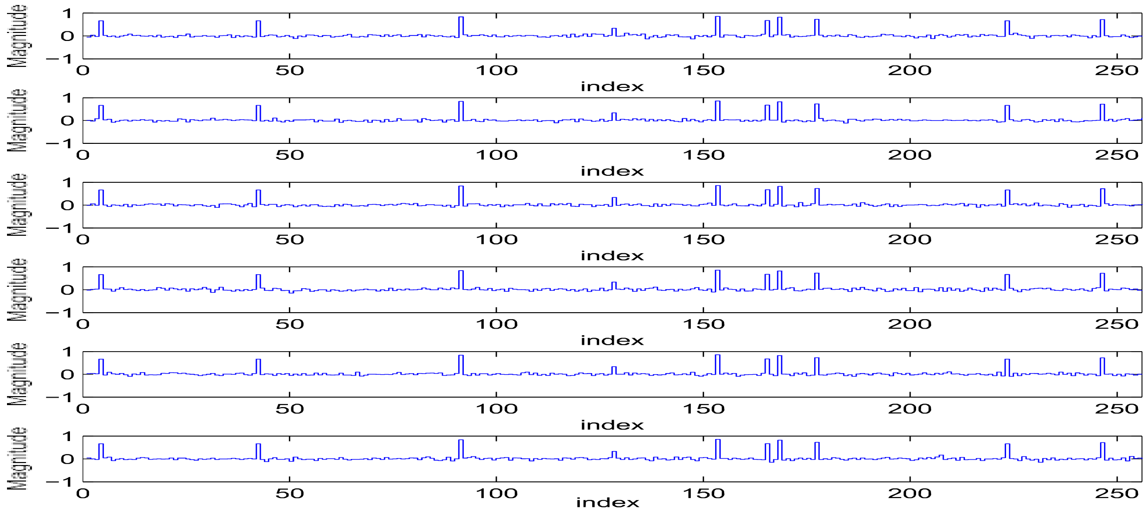

FIGURE 4.10.5. Estimation of x_{200} using DCIF-PM.

Fig.4:15:5. Gives the instantaneous estimate values from all sensor nodes using the DCIF-PM at time k =200.It is clearly shown that the DCIF-PM is erroneously sampling signal component in the zero-component region.

To obtain the square root of matrix, the computational complexity of algorithm is up to $0(\square^{2})$ following the similar treatment.

4.4. Findings

From the performance of the algorithm, Signal fusion center was found to be a critical improvement in designing a WSN.the reason is that information signal fusion was that it can used to extend the network lifetime, the signal fusion center employed in the design of the algorithm deals with multi dimensional signal from sensors that can ideal in real time applications.

Compared to all other algorithms, algorithms based on signal reconstruction with signal fusion centre increased signal convergence rate hence reduced energy consumption, this reduced Multi sensor signal fusion offers increased reliability and high processing gain in overall performance signal with very low SNR hence high energy saving compared to other algorithms.

It was also noted that the performance is achieved with far fewer measurements than the unknowns($<$ *30%*). In addition, only the square-root form of matrix, which is lower triangular matrix, is involved in the algorithm. It directly corresponds to the reduction in the energy consumption of the storage and the communication.

It was demonstrated that the algorithm developed is effective with a far smaller number of measurements than the size of the state vector. This very promising in the WSNs with energy constraints, and the lifetime of WSNs was prolonged.

4.5. SUMMARY

In this Chapter, A Distributed signal reconstruction algorithm is developed by employing compressive sensing and consensus filter to solve as parse signal reconstruction issue in fusion centre WSNs with energy efficiate considered. In particular, ,the pseudo-measurement (PM) technology is introduced into the cubature Kalman filters (CKF),and a sparsity constraint is imposed on the nonlinear state estimation by CKF.In order to develop a distributed reconstruction algorithm to fuse the random linear measurement from the nodes in WSNs,the PM embedded CKF is formulated into the information form, and then derived information filter is combined with consensus filter, while the square-root version is further developed to improve the performance and strength power saving capability.

The simulation result demonstrates that the sparse signal can be reconstructed with fewer nodes in decentralized manner and all the nodes can reach consensus, while providing some attractive benefit a to the green communication

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.0. Introduction.

This chapter gives a summary of the research findings, the conclusions made thereof and the recommendations that the researcher provided on Green Distributed signal reconstruction Algorithm in WSNs.

5.1. DISCUSSIONS

A number of various KF-based distributed estimation algorithms have recently been proposed. In particular, the distributed Kalman Filter (DKF) using the dynamic average-consensus strategies to the weighted measurements and the inverse-covariance matrices has been developed in and for linear system. Assuming the transfer matrices to be sparse and localized, an efficient distributed algorithm has been developed.

Although distributed algorithms to achieve consensus have received a lot of attention as discussed in the literature review, because of their capability of reaching optimal decisions without the need of a fusion center, the price paid for this simplicity is that consensus algorithms are inherently iterative. As a consequence the iterated exchange of

Data among the nodes might cause excessive energy consumption. Hence, to make consensus algorithms really appealing in practical applications, in this case it is necessary to minimize the energy consumption necessary to reach consensus. Signal based fusion center play a fundamental role in determining the convergence rate. Signals from different sensors are combined to create a new signal with a better signal to noise ratio than the original signal.

As the network connectivity increases, so does the convergence rate. However, a highly connected network entails a high power consumption to guarantee reliable direct links between the nodes. On the other hand, if the network is minimally connected, with only neighbor nodes connected to each other, a low power is spent to maintain the few short range links, but, at the same time, a large convergence time is required. Since what really matters in a WSN is the overall energy spent to achieve consensus, it was considered the problem of finding the signal fusion center that minimizes the overall energy consumption, taking into account convergence time and transmit powers jointly.kalman filters in the study is used to fuse low level redundant data,Multi sensor signal fusion offers increased reliability and high processing gain in overall performance signal with very low SNR (smaller than 5dB) can be discarded from signal fusion.

From the performance of the algorithm, Signal fusion center should be considered a critical step in designing a WSN.the reason is that information signal fusion can be used to extend the network lifetime, the signal fusion center employed in the design of the algorithm deals with multi dimensional signal from sensors. It can be used in real time applications (Case study).

This research focused on minimizing and optimizing energy consumption based on the energy consuming constituents as a general model for WSN deployment. Most of the energy is consumed during the sensing, data processing, data storage, and communication phases. The algorithm deals with all aspects of energy consumption in all types of WSNs. We believe reducing the number of measurements by each sensor, means reduction in the data dimensionality of the above mentioned phases, which improve the energy efficiency by reducing the energy consumption of the WSNs and will bring green practice to the WSN communication system.

5:2.CONCLUSIONS

From the green perspective, a distributed nonlinear state estimation algorithm with the signal fusion center for the WSNs has been developed in this study that utilizes advantages of compressive sensing, signal fusion center and the square-root decomposition techniques to improve energy efficiency. By embedding the pseudo-measurement technology into the cubature Kalman filter and corresponding information filter, the authors have derived the CIF-PM algorithm and its square-root version by using the QR decomposition. Meanwhile, the distributed algorithm DSCIF-PM is developed by means of high-pass consensus filter. The developed algorithm can potentially reduce the number of measurements, data storage and communication overhead without degrading the reconstruction performance. The performance of the algorithm was evaluated by simulations. The results have demonstrated that the DSCIF-PM provides satisfactory estimations of sparse signal by using far fewer measurements than required traditionally. It corresponds to energy savings in the WSNs promising positive contribute to the green 5G.

5.3. CONTRIBUTION TO THE KNOWLEDGE

Temporal coverage pose limitation to WSNs, temporal coverage depends on the sensor sampling rate, communication delay and the node duty cycle (see the literature review).Temporal coverage can be understood as the ability to fulfill a network purpose during its life time. Due to redundancy and cooperation properties, WSNs are composed of large number of sensors nodes posing scalability challenge caused by a potential collision and transmission of redundant data.

Introduction of signal fusion center in the WSNs communication network algorithm played a key role in the reduction of overall communication load in the network by avoiding transmission of redundant signals to increase the lifetime of the sensor node.

5.4. RECOMMENDATIONS FOR FUTURE RESEARCH

Researchers have discussed sparse state estimation problem within the framework of the Kalman filter for linear dynamical system. In nonlinear dynamical case, the studies have attempted to discuss the sparse state reconstruction based on nonlinear filter. Nevertheless, the distributed sparse state estimation for the nonlinear system has not been adequately investigated yet to the best of my knowledge. Therefore further CS reconstruction procedures should to be conducted to see whether we can further reduce the number of sample required. The computational complexity of CS/DCS encoding is not significant, but decoding complexity ($O(n^3)$) can be. Due to decoding complexity, CS/DCS might not be suitable for real-time applications employing large WSNs. Investigation of decoding complexity reduction for CS/DCS is a recommended future research direction. Algorithms based multi sensor signal fusion in multipath fading communication channel needs further investigations

5.3.1. Dependent signal fusion exploiting CS.

Dependent data fusion exploiting CS; Dependence is one of the common characteristics exhibited in multiple sensor data. While there exist several recent works that exploit dependence in the Bayesian CS framework under restricted assumptions, CS based dependent signal fusion especially in the presence of non-Gaussian and the spatio-temporal dependence is not well understood. Thus, exploitation of higher order dependence and structured properties of high dimensional data in CS based fusion is worth investigating.

5:5.POLICY RECOMMENDATION.

Prison is the place that holds and transforms criminals; safety is the first of all to quarantee.To protect the safety of society, and to protect personnel and stability of guards and detainees. By installing Green energy security monitoring system, it can effectively strengthen the management of prisoners and the reduce overall energy cost and create a toxic free environment.

To strengthen security measures and strengthen prison modernization, putting forward a kind of prison security system design scheme based on wireless sensor network (WSN).). Kenya government should review the Information, Communication, and technology policy to take into consideration emerging technological innovation for growth of the Sector, for example Sensor Network. The government, require to formulate policies to address deployment of sensors, privacy of the information to individual and institution that are not captured in the current policy documents.

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APPENDICES

APPENDIX A: MODEL THEORY

To each symbol f is associated a number □(□) $\in \mathbb{N}^{>0}$,and to each relation symbol *R* a number □(□) ∈ □.(arities of the function *f*, resp, the relation *R*)

We fix a language □ = {□□, □□□□| □ ∈ □, □ ∈ □, □ ∈ □}, Where the □□ function symbols, the □□ are relation symbols, and the □□ are constant symbols

The structure □ is the denoted by

□ = (□, □□□, □□□, □□□|□ ∈ □, □ ∈ □)

L-structures. We fix a language $L = \{f_i, R_j, c_k \mid i \in I, j \in J, k \in K\}$, where the f_i*’s* are function symbols, the R_j *’s* are relation symbols, and the c_k*’s* are constant symbols.

APPENDIX B: THE KALMAN FILTER

Nonlinear Approximation Error.

The extended Kalman filters generally has better robustness because it uses linear approximation over smaller ranges of state trajectory perturbation plus state estimation errors,wheres the extended Kalman filters assumes linearity only over the range of state estimation errors. The expected squared magnitudes of these two ranges can be analyzed by comparing the solutions of the two equations.

$$\square_{\square+1} = \square_{\square}^{[1]} \square_{\square} \square_{\square}^{[1]\square} + \square_{\square}$$

$$\square_{\square+1} = \square_{\square}^{[1]} \{\square_{\square} - \square_{\square} \square_{\square}^{\square} [\square_{\square} \square_{\square} \square_{\square}^{\square} + \square_{\square}]^{-1} \square_{\square} \square_{\square}\} \square_{\square}^{[1]\square} + \square_{\square}$$

The first of these is the equation for the covariance of trajectory perturbation, and the second is the equation for the priori covariance of state estimation errors. The solution of the second equation provides an idea of the ranges over which the extended Kalman filters uses linear approximation. The sum of the solutions of the two equations provides an idea of the ranges over which the linearized filters assumes linearity. The non linear approximation error can be computed as function of perturbation (for linearized filtering) or estimation errors (for extended filtering) $\square\square$ by the formulas

$$\square_{\square} = \square(\square + \square\square) - \square(\square) - \frac{\square\square}{\square\square} \square\square$$

$$\square_{\square} = \bar{\square} \left(h(\square + \square\square) - h(\square) - \frac{\square h}{\square\square} \square\square \right)$$

Where $\square_{\square}$the error in the temporal is update of the estimated state variable due to nonlinearity of the dynamics and $\square_{\square}$ is the error in the observational update of the estimated state variable due to nonlinearity of the measurement. As a rule of the thumb for practical purposes, the magnitude of these errors should be dominated by the RMS estimation uncertainties. That is $|\square|^2 \ll$ trace P for the ranges of $\square\square$ expected in implementation

Mean squared error.

Many signals can be described in the following way;

$$\square_{\square} = \square_{\square} \square_{\square} + \square_{\square}$$

Where; $\square_{\square}$ is the time dependent observed signal, $\square_{\square}$is the gain term, $\square_{\square}$ is the information bearing signal and $\square_{\square}$ is the additive noise

The overall objective is to estimate$\square_{\square}$. The difference between the estimate of $\hat{\square}_{\square}$ and $\square_{\square}$ itself is termed the error;

$$\square(\square_{\square}) = \square(\square_{\square} - \hat{\square}_{\square})$$

The particular shape of $\square(\square_{\square})$ is dependent upon the application, however it is clear that the function should be both positive and increase monotonically. An error function which exhibits these characteristics is the squared error function. An error function which exhibits these characteristics is the squared error function;

$$\square(\square_{\square}) = (\square_{\square} - \hat{\square}_{\square})^{2}$$

Since it is necessary to consider the ability of the filter to predict many data over a period of time a more meaniful metric is the expected value of the error function;

$$\square\square\square\square\square\ \square\square\square\square\square\square\square\square\square = \square\big(\square(\square_{\square})\big)$$

This result in the mean squared error (MSE) function

$$\square(\square) = \square(\square_{\square}^{2})$$