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Context-Aware Energy Management System for Data Acquisition in Wireless Sensor Networks

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Abstract:
Energy management for wireless sensor network (WSN) has become a critical research interest mainly due to its energy constraint. A typical WSN node has three major power consuming sub-units namely; data acquisition, computation and communication. The amount of energy consumed by these sub-units can be minimized through the use of energy management techniques and algorithms. However, this research is aimed at designing a Context-aware energy management system for WSN with focus on the data acquisition sub-unit. A Context-aware and Energy-efficient Data Acquisition Reconfiguration Algorithm (CAEEDARA) was developed with context limited to the node available battery energy and sampled inputs obtained. The context information along with the obtained input characteristics forms the basis for node reconfiguration behavior decision which includes varying sampling frequency and computing sampling interval. The WSN node architecture include several low-power components such as gas sensors for monitoring carbon dioxide CO_2, methane CH_4 and nitrogen dioxide NO_2 (Gascard NG and Graphene-based) interfaced with a microcontroller unit (MSP430F2272) for processing acquired data samples, a ZigBee module (ZE51-2.4) remote data communication and transmission. The developed CAEEDARA algorithm was domicile at the base station (BS) due to its access to unlimited energy. The operation of the developed CAEEDARA algorithm was simulated using MatLab 2018b running on a Dell Intel Core i3 processor, and the performance evaluation metric was based on its duty cycle and energy consumed. Simulation results showed that the CAEEDARA algorithm saves about 80% of the node battery energy thus resulting in a prolong node life.

INTRODUCTION

A context-aware system is a system that has the ability to gather information about its environment at any given instant of time and adapt its behavior accordingly. Context awareness involves two stages which are to obtain context and to adapt to context (Engelenburg *et al.*, 2019). Thus, context-aware systems are designed to adapt system operations to context without explicit user intervention considering the context where it operates in order to increase its usability and effectiveness (Baldauf *et al.*, 2007). Context-aware systems are categorized into local and distributed systems [3]. Local systems have the sensors and applications to be tightly coupled while the distributed systems have the sensors and applications loosely coupled. In designing a context-aware system, all elements of the context where the system operates have to be clearly defined before its design. During operation, a context-aware system employs the use of context instances which can be external or internal. An external instance involves a physical dimension such as light, temperature etc. that can be measured by hardware sensors, while the internal instance is dimension such as goal, emotional state, and task mostly specified by the user or captured by monitoring the user interaction (Baldauf *et al.*, 2007). Context information can be obtained either by applying sensors, through network information and device status. This information is particularly useful in ensuring efficient energy management for wireless sensor network (WSN) systems embedded with one or more context-aware features.

A WSN network is a distributed interconnected network of multiple low-power sensor nodes, which communicates together to achieve a common purpose. It designs usually incorporate knowledge and technologies obtained from wireless communication, networking and systems, and control theory (Fishione, 2014). Some applications of WSN include are but not limited to environmental monitoring, object tracking, fire and disaster management, agriculture, building structure monitoring. Its vast application area is due to the low cost of deploying nodes, its ability to communicate wirelessly, its compact size and its ability to operate autonomously in remote environments where human access may not be possible. WSNs are known to have critical design issues such as energy management, autonomous management, data acquisition, limited memory and storage space, transmission and much more (Sharma *et al.,* 2013). These issues are mainly because the nodes employed in WSN designs are resource constrained. A typical WSN network consists of three components namely, the node(s), sink and the base station (BS). The node which includes one or more sensors interfaced with a microcontroller unit and a communication module convert physical quantities such as temperature, pressure, and even gases into electric signals, while the sink collates and transmits the obtained signals from the various nodes through an entire network in a way that makes communication possible. The BS analyzes the data transmitted signals from the sink(s) and making appropriate decision when necessary. A node has three major power consuming sub-units namely; data acquisition, computation and communication. Each sub-unit is designed to perform a particular task and contributes to the overall power consumption of the node. Nodes are mostly battery powered as such they have limited energy which implies a short node life. The lifetime of a node depends largely on the amount of energy consumed by all three-power consuming sub-units. Hence, in the design of node architecture, emphasis is placed on extending the node lifetime as much as possible (Enami *et al.,* 2010). Minimal energy consumption during its operations can be achieved through the deployment of an efficient energy management scheme and protocols so as to prolong the node lifetime.

Energy management schemes and protocols are majorly grouped into three categories which are duty-cycle, data-driven and mobility-based (Nithya, 2015). Each of these categories has their sub-categories. However, this for the purpose of this research, only the data-driven category will be expounded upon as it is the basis on which the development energy management scheme is proposed. The data-driven scheme conserves the node energy by first sorting out any unwanted samples to prevent energy wastage, after which it prevents them from, been forwarded to the BS. Next, it further minimizes the amount of energy consumed by ensuring the accuracy of the data obtained by the node to a reasonable level. Its sub-categories are data reduction and energy efficient data acquisition. Data reduction scheme reduces the amount of data to be transmitted to the BS using any of these three techniques in-network processing, data compression, and data prediction (Nithya, 2015). Energy efficient data acquisition scheme minimizes energy by reducing the number of acquired samples employing hierarchical sampling, adaptive sampling, or model-based approach (Nithya, 2015). In the hierarchical sampling, different types of sensors are used in the node architecture with each characterized by its accuracy and associated energy approach which usually determines which sensor is to be activated so as to maintain a balance between accuracy and energy consumption. Adaptive sampling scheme exploits the similarities that are present in the sensed data while considering the available battery energy to ensure a reduction in the amount of acquired data from the transducer. Lastly, the model-based scheme builds a model of the sensed phenomenon on sample data which serve as the basis on which the next data can be predicted, thus reducing the number of data sampling and the amount of data communicated to the BS.

In addressing energy management concerns for the data acquisition sub-unit which has been identified to be under explored [8], several researchers have developed adaptive sampling algorithms to adapt sampling frequency and sampling interval to certain dynamics based on Fast Fourier Transform (FFT), environmental conditions, input characteristics and so on. However, the deployment of these adaptive sampling algorithms has not completely settled the concerns for efficient energy management for data acquisition operations, hence the need for further studies in the research area. Based on the aforementioned, this research proposes a context-aware energy management system for wireless sensor network to minimize node energy consumption while acquiring data samples.

RELATED WORKS

Over the years, several attempts through research have been made to address energy management issues as it relates to WSNs. These researchers have employed various energy management schemes and techniques based on duty-cycle, data-driven and mobility-based approaches. These efforts have achieved relative energy management at both the node and network levels, thus prolonging the operating lifetime of the sensor network.

Sinha and Chandrakasan (2001) developed an operating system (OS) directed dynamic power management (DPM) technique to improve the energy efficiency of sensor nodes without significantly degrading performance. The node architecture comprises of embedded sensor, analog-digital converter, a processor with memory (StongARM SA-1100 processor) and the RF circuits. Each component in the node is controlled by a micro-operating system (µOS) through micro-device drivers which decides when the devices are to be turned ON and OFF. Test results proved that the developed OS efficiently manages energy consumed at the computation and communication units but is unaware of its context.

Sharma *et al.*, (2008) developed an optimal energy management policy for energy harvesting sensor nodes. The energy management policy was used during the wake period of the sleep-wake cycle and at the multiple access channel (MAC) employed by the energy harvesting sensor nodes. Simulation results show that the system functions appropriately in energy neural operation with the use of optimal throughput and mean delay which results in efficient energy management, however, the system lacks context-awareness.

Alippi *et al.*, (2010) developed an adaptive sampling algorithm (ASA) for snow monitoring applications that initializes its sampling frequency by performing a Fast Fourier Transform (FFT) on a sequence of pre-sensed data to obtain its maximum frequency. A new maximum sampling frequency is obtained depending on the sequence of subsequently data. To obtain the new sampling frequency, the variation of the current sampling frequency is compared with the new maximum frequency for the current phase of sampling. Simulation results proved that the developed ASA reduced the number of acquired samples by about 79% compared to the traditional fixed-rate approach, thus achieving a remarkable energy management. However, the developed ASA lacked context-awareness as the node context was not considered in the decision to adapt sampling frequency and interval.

Jelicic, (2011) developed a state-of-the-art power management scheme which employs duty-cycling and a separate wake-up receiver technique for hierarchical, heterogeneous, multimodal WSNs designed for smart video surveillance and smart gas detection. The developed technique was tested and proved to relatively achieve energy management for communication and sensing operations, but lacked the flexibility and context-awareness required to efficiently drive pervasive systems for effective energy management.

Chaudhary *et al.*, (2012) developed an efficient and effective architecture and energy efficient techniques for data aggregation and data collection in WSN using global weight calculation of nodes principle and data cube aggregation technique. The architectural model includes the selection of group of nodes and the subsequent division of the nodes into clusters. Each cluster satisfies a set of parameter requirements which are required to determine the number of nodes present in a cluster. Cluster heads (CHs) selection are done, with the CHs aggregating the data collected to prevent unnecessary energy loss. Test analysis proved that accurate battery usage and low power consumption was achieved; however, the system lacks context-awareness.

Asorey *et al.*, (2013) developed a hierarchical network architecture where nodes with renewable energy sources (primary nodes) perform the most message delivery tasks while nodes with conventional chemical batteries (secondary nodes) perform less communication demands. An optimization framework was included in the design to calculate the optimal assignment of the renewable energy supplies to maximize network lifetime, obtain minimum number of energy supplies and node assignment. An algorithm called OPT-PRIM which approaches the results of the optimization framework was presented. The test results proved that OPT-PRIM algorithm generates a much faster execution speed resulting in efficient energy management. The effect of node context was not considered in the algorithm development.

Qi (2013) developed ASA for wireless body sensor network called AdaSense. A generic programming algorithm was developed, and the system uses it to determine the optimal sensor sampling rate by reducing the acquisition rate that is required in the detection of an activity event and multi-activity classification. Simulation results showed that the amount of energy consumed was minimized, however, the developed ASA did not consider the node context while obtaining its optimal sampling frequency.

Hoang (2014) developed a novel design for WSN to reduce energy consumption and increase network dependability. The design integrates a smart Power and Availability Manager (PAM) device in the node system. The PAM monitors power and energy based on Dynamic Power Management (DPM) and Dynamic Voltage and Frequency Scaling (DVFS) policies. Different scenario tests of hazardous gas detection application were performed using CAPNET-PE tool to establish the extent of energy gain. The tests showed that DPM and DVFS techniques provides a significant energy gain ranging from 72% when event rate is low to 35% when event rate is high, with an energy overhead of about 0.01% over total node energy consumption, but lacked context-awareness required to establish it influence on the node energy consumption behavior.

Visconti *et al.*, (2016) developed a solar-based harvesting board system based on LTC3330 IC to sustain the energy of a Medimote sensor node developed by Medinok SPA. Based on the LTC3330 IC technical features, a complete circuit diagram for energy harvesting and power management was designed to ensure power supply of the WSN node and optimal exploitation of available energy. Experimental results showed that the developed board allowed for the control and tracking of the maximum power point (MPP) of the energy source connected to the input thus energy efficient energy management but neglected the role of context in extending the node lifetime.

Jon (2016) developed ASA for air pollution monitoring application based on computation via statistical means. The developed ASA uses Kalman filter to removes noise from the sensor data and adjusts sampling interval (SI) based on the difference between its present and previous data input. If the sampling interval is within the sampling interval range, a new sampling interval is used for the next measurement; otherwise, the server assigns a new sampling interval and sampling interval range for the node. Simulation results show that the developed ASA significantly decreases the number of transmissions while providing a relatively fine data quality. However, the developed ASA ignored the node context in adapting sampling frequency and interval.

Shao *et al.*, (2019) developed a distributed dynamic power allocation strategy based on energy balance to improve energy efficiency for WSN. The transmission power of nodes and the energy of the next hop node are changed dynamically through the exchange of local information between neighbour nodes. Based on the information received, the best node is selected to forward data. The next hop node and the corresponding power are dynamically adjusted according to the situation given that the energy of the nodes decreases gradually. Simulation results performed using MatLab software showed that the strategy achieved more balanced overall energy consumption and prolong survival network lifetime, but failed to address the effect of context in dynamically adjusting the node power.

Naji *et al.*, (2019) developed an energy management system (EMS) that employs WSN for data acquisition in a smart energy-efficient building (SEEB). EMS depends greatly on context recognition for HVAC (heating, ventilation and air conditioning system) control so that the more precise the context is, the more accurate is the decision taken by the EMS. The energy-aware context recognition algorithm (EACRA) developed dynamically configures the sensor nodes to send only specific data under specific conditions and time. Experimental results showed that a minimal amount of energy was been consumed when sampling is done based on the developed algorithm as against the periodic sampling employed by traditional approaches. However, the developed algorithm did not consider internal context parameters in its dynamic configuration.

Naji *et al.*, (2020) developed a wireless sensor network (WSN) based energy management system (EMS) for a real-world smart building on a university campus. The proposed EMS employs the Context-Based Reasoning (CBR) model to represent different types of campus buildings and offices. Finite state machine (FSM) strategies were used to implement the new energy efficient policy for the electrical heaters control while leveraging on context-related events. In order to optimize the sensor's battery lifetime, a new energy aware control recognition algorithm (EACRA) was employed to dynamically configure the sensors to forward data under specific conditions and at specific times. Testing of the designed EMS using the Plan-Do-Check-Act (PDCA) proved that EACRA increases the sensor battery lifetime by optimizing the number of samples, used modules and transmissions. Its context-aware feature is limited to external parameters with the internal parameters not looked into.

METHOD

This section presents the proposed system model for the context-aware energy management system for data acquisition in wireless sensor network. This system consists of several sensor nodes with each node comprising of an MSP430 microcontroller, gas sensors (Gascard NG and Graphene) and a ZE51-2.4 communication module. The circuit diagram was presented using Proteus, the proposed CAEEDARA algorithm code was presented using C programming language tool while MatLab Simulink was used to model the proposed system.

System Design and Implementation

The architecture of the proposed context-aware energy management system is presented as in Figure 1. The energy management system architecture has two modules namely; the monitoring field and the remote monitoring center.

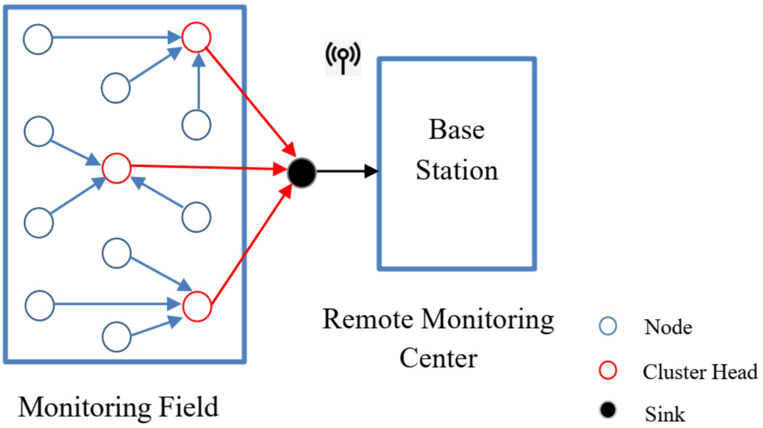

Fig 1: Context-Aware Energy Management System Architecture

The monitoring field module comprises of several sensor nodes which is integrated with embedded wireless sensor technology through an MSP430 microcontroller, a Gascard NG and Graphene gas sensors and a ZE51-2.4 communication module. The second module is identified as the remote monitoring center where the entire field data are processed and stored with appropriate reconfiguration decision made to minimize the number of acquired samples and transmissions.

The Monitoring Field Module

This module comprises of three components such as sensor node, cluster heads and sink. Each sensor node has two sensors namely Gascard NG and Graphene sensors to detect and measure the concentration of three gases which are carbon dioxide (CO_2), methane (CH_4) and nitrogen dioxide (NO_2) in an outdoor environment. The Gascard NG sensor is used to detect and measure the concentration of CO_2 and CH_4 while the Graphene sensor is for NO_2. Both sensors are connected directly to the MSP430 microcontroller for the acquisition of data and onward relay to the remote monitoring center through the ZigBee communication module. Figure 2 illustrates the block diagram of the node architecture as deployed in the monitoring field.

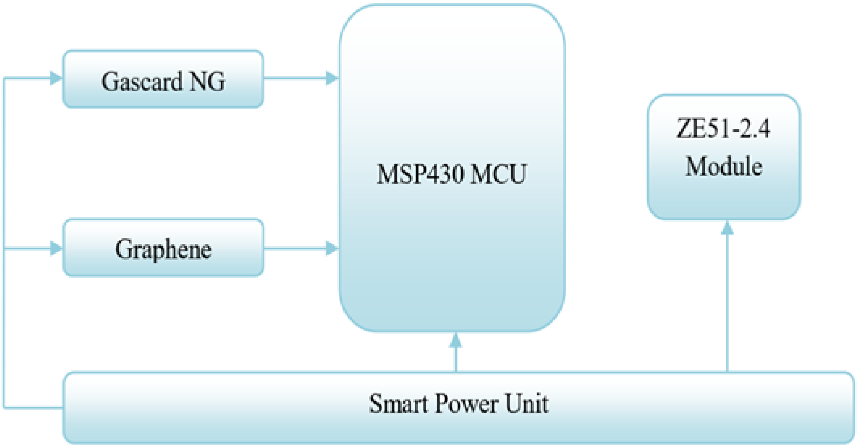

Fig 2: Block Diagram of Sensor Node Architecture

The various components in Figure 2 are interfaced and powered by the smart power unit. The smart power unit has a battery power source of 4.5 V as shown in the circuit diagram of the sensor node architecture illustrated in Figure 3. The monitoring field is divided into clusters, with each cluster having a cluster head (CH). The CHs collects data from their member nodes and then forward to the sink, which perform data aggregation on it to eliminate redundant data to reduce the number of acquired samples. After which the sink then forwards the sampled data to the base station (BS) located in a remote monitoring center. The context information (available battery energy level) which is available at the smart power unit is also been forwarded to the base station (BS) for appropriate reconfiguration action.

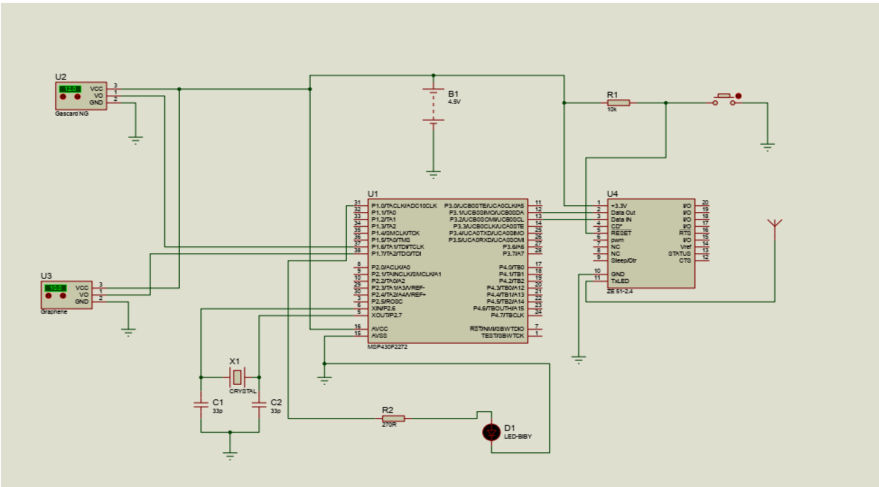

Fig 3: Circuit Diagram of Sensor Node Architecture

The Remote Monitoring Center Module

This module is responsible for storing and processing the received sensed data because of its access to unlimited power supply. Based on the generated result obtained from processing appropriate reconfiguration action is executed. The reconfiguration action could be to increase/decrease sampling frequency and sampling interval or out rightly maintaining the initial/previous startup sampling frequency and sampling interval. An administrator is also physically present at the remote monitoring center to visually monitor the energy behavior of each node using a developed BS application interface. However, the BS runs the proposed adaptive sampling algorithm (ASA) which is the basis on which reconfiguration decisions are made.

Context-Aware Energy-Efficient Data Acquisition Reconfiguration Algorithm

The proposed context-aware and energy-efficient data acquisition algorithm (CAEEDARA) was developed following a five-step approach as represented in Figure 4.

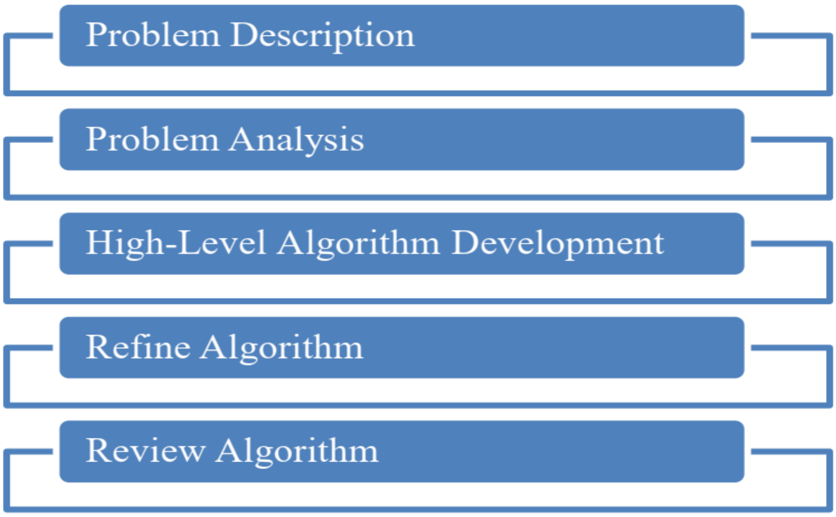

Fig 4: Five Step Approach for Algorithm Development

Problem Description:

As the first step of the algorithm design process, it involves identifying and obtaining a description of the problem. The identified problem is the limited energy constraint inherent in WSN node since they are mostly battery powered. From [8] minimal energy conservation was majorly tailored to address computation and communication operations with data acquisition operation been under explored.

Problem Analysis:

During the problem analysis, several approaches were observed to have been used to minimize energy consumption when the node acquires data. One of such approach is the use of adaptive sampling algorithm which may consider one or more pre-dynamics. Some of these pre-defined dynamics are self-adaptation, online estimation, and input characteristics. This work is based on input characteristics alongside the node available battery energy. The start-point for analyzing the problem using input characteristics dynamic is to keep track of the sensed input values and its time stamp, after which the end-point is activated which involves adapting the node sampling frequency and computing sampling interval based on the available battery energy.

High-Level Algorithm Development:

The high-level algorithm development was broken down into the several high-level representations such as: Initialize node, obtain last input value, read node input, compute difference between sampled values, store new input, obtain current battery level of node, establish the significance of the difference between inputs adapt sampling frequency and lastly compute sampling interval. The flowchart for the high-level algorithm is as illustrated in Figure 5.

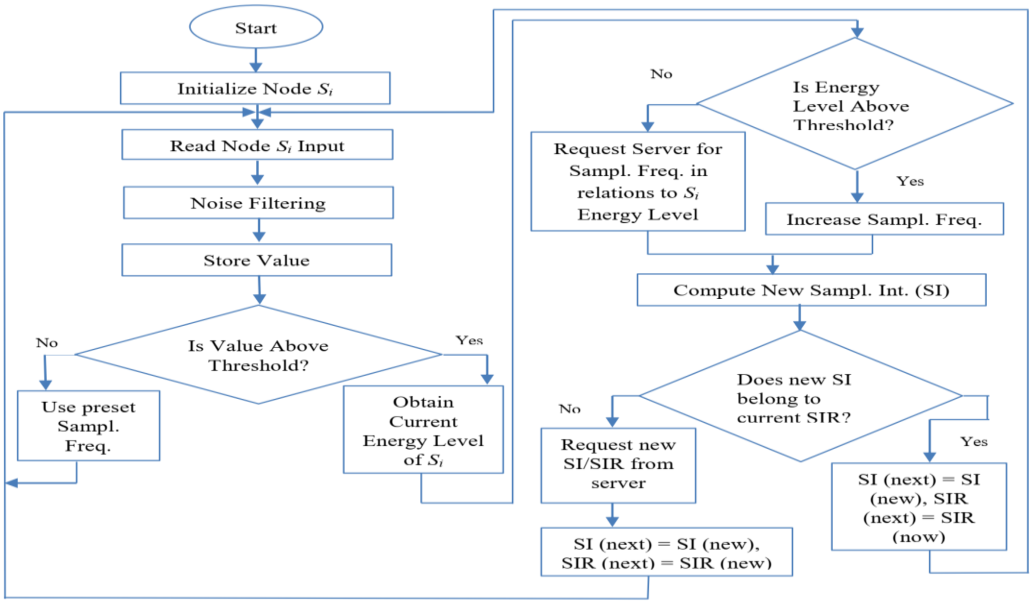

Fig 5: Flowchart for the Developed CAEEDARA algorithm

Refining the Algorithm:

The high-level algorithm was then refined by adding other relevant details to generate the pseudo code as presented in Figure 6.

```
While (true)
Si_last = Last Sensor Output
Ti_last = Last Time Stamp
Si = Sensor Output
Sni = Extended_Kalman_Filter (Input Si, Input Fs) // Sni = Filtered Si
Sdiff = Sni–Sli
Tn = New Time-Stamp
If Sdiff Significant (Sdiff> Threshold)
EL = Energy_Level_Monitor() // where EL = Battery Level
If EL > Threshold
Fs = Fs + 1 // Increment Fs, where Fs is Sampling Frequency
SIR (New) = Compute_New_SI (Input Fs) // Function to Compute New Sampling Interval
(SI)
else
Fs = IN Adjusted Fs from Server
SIR (New) = Compute_New_SI (Input Fs)
Tsample = Last-Time-Stamp-for-Sampling
else
// Do Nothing
Sli = Sni
T1 = New Time-Stamp
end
Functions / Subroutines
Extended_Kalman_Filter()
Compute_NewSI()
```

Fig 6: CAEEDARA Pseudo Code

Review the Algorithm:

a step by step working through was done to determine whether or not the developed CAEEDARA algorithm was able to solve the identified problem.

RESULTS AND DISCUSSION

The simulation of the developed CAEEDARA algorithm was done using MatLab 2018b with real-life data obtained from the field. The threshold values for the three monitored gases (carbon dioxide, methane, nitrogen dioxide) are presented in Table 1.

Table 1: Threshold Values for the Simulation

Metric\Gas	CO_2 (ppm)	CH_4 (ppm)	NO_2 (ppm)
Threshold	25	55	15

The parameter settings for the node behaviour simulation as obtained from the range evaluation are presented in Table 2.

Table 2: Simulation Parameter Setting

CO_2 Range	CH_4 Range	NO_2 Range	Battery Level (Volts)	Maximum Sampling Frequency (Hz)	Initial Setup Sampling Frequency (Hz)	Initial Sampling Interval (second)
22.0	52.0	14.0	4.5	16.0	8.0	3.5

Several sensors read were obtained for the three gases and their data presented in Table 3, Table 4, and Table 5.

Table 3: CO2 Simulation Values

Sample Number	Sample Value (ppm)
1.	399.16
2.	379.34
3.	387.21
4.	379.96
5.	398.42
6.	377.76
7.	394.39
8.	395.30
9.	396.41
10.	379.48
11.	386.29
12.	383.27
13.	394.93

A total of thirteen samples of CO2 were obtained per sample time (1.1 seconds) with a variance of 8.08. The range is evaluated to be 21.40 and it is within the gas limit set at 25, with no deviation from the predefined threshold, the last reading which is 394.93 ppm was then stored on the BS and the developed algorithm proceeded to sense the second sensor (CH4) to obtain its reading. The simulation values for CH4 are presented in Table 4.

Table 4: CH4 Simulation Values

Sample Number	Sample Value (ppm)
1.	1811.50
2.	1836.30
3.	1798.60
4.	1802.80

5.	1796.70
6.	1796.20
7.	1834.20
8.	1819.20
9.	1817.60
10.	1796.70
11.	1833.30
12.	1821.40
13.	1807.30

The values presented in Table 4 indicated that thirteen samples were also obtained per sample time with a variance of 14.98. The range is evaluated as 40.10 and is within the gas limit set at 55; hence, since there is no deviation from the threshold, the last reading which is 1807.30 is stored in the BS. Finally, the developed algorithm then proceeded to check for the concentration of the last gas which is NO2. The simulation values for NO2 are presented in Table 5.

Table 5: NO2 Simulation Values

Sample Number	Sample Value (ppm)
1.	325.65
2.	324.11
3.	319.59
4.	321.86
5.	320.25
6.	321.09
7.	321.86
8.	324.32
9.	319.22
10.	331.06
11.	331.64
12.	325.34
13.	325.32

Table 5 represents the thirteen simulated values for NO2 obtained per sample time with a variance of 3.96. The range is obtained to be 12.41 and it is within the gas limit set at 15, hence, since there is no deviation from the threshold, the last reading which is 325.32 is stored in the BS. It can be observed that all three gas sensors had their first read range values within their various range thresholds as such the preset sampling frequency and sampling interval were maintained for the next round of sampling to promote efficient energy management. The overall total sample time for sensing the three gases is approximately 3.5 seconds. The BS can implement an adaptive duty cycle on the node depending on the stability of the gas concentration being sampled.

The total energy consumed by the node operating modes (active and sleep) is obtained using Equation 1, 2 and 3 giving the microcontroller parameters presented in Table 6.

$$E_T = E_{act} + E_{sl} \quad (1)$$

$$E_{act} = I_{act} \times V_{batt} \times t\ (s) \quad (2)$$

$$E_{sl} = I_{sl} \times V_{batt} \times t\ (s) \quad (3)$$

Table 6: Microcontroller Parameters

Notation	Parameter	Value
C_{sleep}	Sleep Current (µA)	0.7
C_{active}	Active Current (µA)	270
C_{off}	Off Current (µA)	0.1
$C_{wake-up}$	Wake-up Current (µA)	< 1
$C_{battery}$	Battery Capacity (mAh)	2500
V	Voltage	4.5
$I_{preamble}$	Preamble Length (bytes)	271
I_{packet}	Packet Length (bytes)	36
t_1	Radio Sampling Interval (s)	100×10^{-3}
R	Sampling Rate (packets/s)	1/300
S_{time}	Sample Time (s)	1.1

So that the minimum and maximum energy values for the operating mode is presented in Table 7 applying the time values presented in Table 6.

Table 7: Time Values for Minimum and Maximum

Node State	Sample Reference	Time (second)
Active	Minimum	3.5
	Maximum	10
Sleep	Minimum	300
	Maximum	3000

Table 8: Minimum and Maximum Energy Values for Sleep and Active Mode

Node State	Sample Reference	Energy (Joule)
Active	Minimum	4.2525×10^{-3}
	Maximum	1.215×10^{-2}
Sleep	Minimum	9.45×10^{-4}
	Maximum	9.45×10^{-3}

The total energy consumed by the node is evaluated and presented in Table 9.

Table 9: Total Minimum and Maximum Energy Consumed by the Node

Energy Limit	Total Energy (Joule)
Minimum (E_{min})	5.1975×10^{-3}
Maximum (E_{max})	2.16×10^{-2}

The duty cycle of the node was computed using Equation 4.

$$\text{Duty cycle} = \frac{\text{Pulse width}}{\text{Time}} \times 100\% \tag{4}$$

Substituting the appropriate values into Equation 4, the lower and upper duty cycle limit is computed to be 1.15% and 0.33% respectively. Therefore, the duty cycle range is said to be between 0.33 and 1.15. Figure 7 shows the correlation existing between the total energy consumed by the node and the duty cycle.

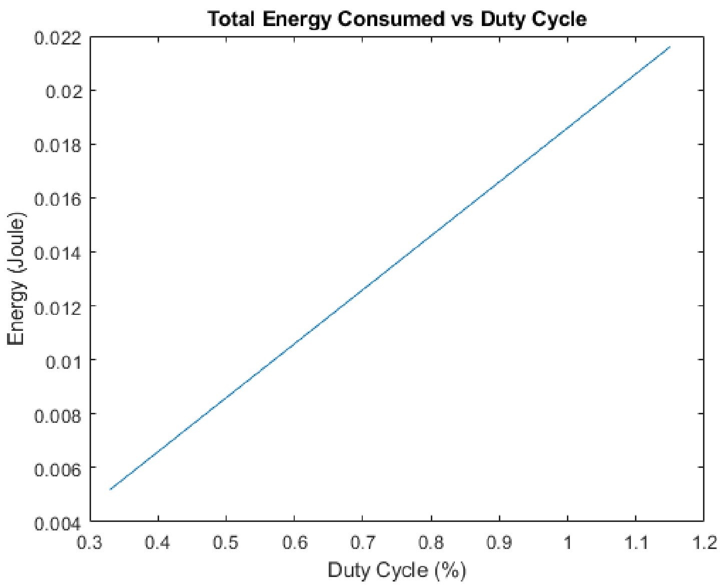

Fig 7: Total Energy Consumed vs. Duty Cycle

From the straight line shown in Figure 7, it can be deduced that the duty cycle implemented by the CAEEDARA algorithm causes the energy consumed by the node to increase linearly. At the upper limit of the duty cycle, the energy consumed by the node is given as 5.1975 × 10-3 J, while at the lower limit of the duty cycle, the energy consumed by the node is given as 2.16 × 10-2 J. The slope of the line was computed using Equation 5.

$$\text{Slope}= \frac{\Delta y}{\Delta x} \tag{5}$$

Substituting the changes in x and y respectively at any given point, the slope is evaluated as 0.02. The positive slope value indicates that total energy consumed and the duty cycle are closely related so that when the duty cycle increases, total energy consumed by the node increases as well. Hence, the node consumes an average of 0.02 Joule for every 1% increase in the duty cycle. The energy consumed and duty cycle performance for the developed CAEEDARA algorithm was compared and validated against the duty cycle of Saraswat and Bhattacharya, (2013) as illustrated in Figure 8.

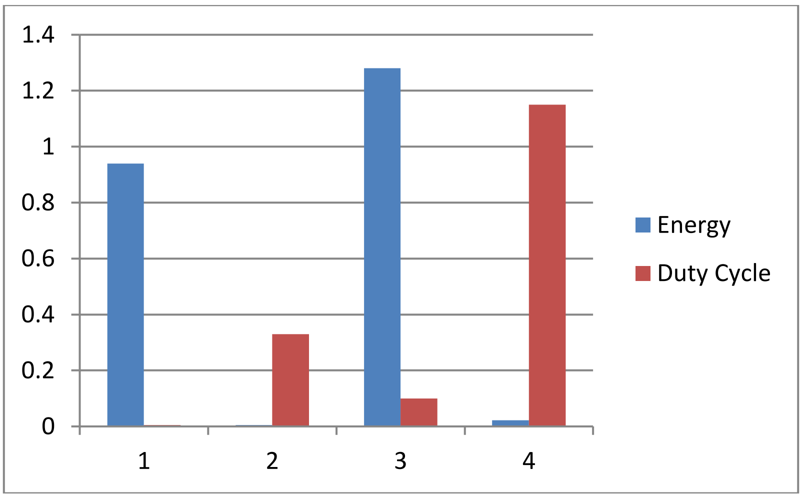

Fig 8: Relationship between Duty Cycles for CAEEDARA and (Saraswat and Bhattacharya, 2013)

Figure 8 shows the total energy consumed and duty cycle for Saraswat and Bhattacharya, (2013) represented as bars 1 and 3 and the developed CAEEDARA represented as bars 2 and 4. Comparing bars 1 and 2, operating at minimum duty cycles, it was observed that Saraswat and Bhattacharya, (2013) duty cycle which is not visible on the plot due to its relatively low value of 0.005 consumed 0.94 J of energy which is far greater than the 0.005198 J of energy consumed by CAEEDARA at a duty cycle of 0.33. Comparing bars 3 and 4 operating at the maximum duty cycles, it was observed that the amount of energy consumed by Saraswat and Bhattacharya, (2013) at a duty cycle of 0.1 is 1.28 J which is also greater than the energy of 0.0216 J consumed by the CAEEDARA system at a duty cycle of 1.15. Hence, the implemented CAEEDARA algorithm outperformed the Saraswat and Bhattacharya, (2013) which although has a longer duty cycle but consumes lesser energy thus resulting in an extended node life. The longer duty cycle implemented by CAEEDARA ensured that the node stay active as much as it is necessary so that critical events are not missed.

CONCLUSION

The development of Context-aware and energy-efficient data acquisition reconfiguration algorithm (CAEEDARA) designed solely to minimize the amount of energy consumed during data acquisition operation of sensor node was able to reduce the amount of energy consumed by the node to about 80%. It is however, recommended that for further research the context-aware feature of the node be designed to include location information to ensure accurate fault detection for multiple node deployment.

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