FLAW DETECTION IN WIRELESS SENSOR NETWORK USING A LDA CLASSIFIER

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Abstract - *In wireless sensor network, wireless sensor fault diagnosis based on fusion data analysis has attracted attention in the wireless sensor field. The different types of faults are detected based on rate of change of sensed data. In order to identify the fault, Fourier transform parameters are also used along with the time, space and attribute. In this paper, fault diagnosis is performed using LDA classifier so that optimization is reduced. As fault is detected, it is very necessary to compensate the fault, hence fault compensation is also introduced to stabilize the faulted data.*

***Key Words*: Wireless Sensor Network (WSN), Belief Rule Base (BRB), Linear Discriminant Classifier (LDA).**

1.INTRODUCTION

As a new information acquisition and processing technology, wireless sensor network (WSN) has been widely used in military, environmental monitoring, intelligent home, complex mechanical control, urban transportation and space exploration. In a complex environment, WSN technology has unparalleled advantages compared with other information access techniques. A typical WSN generally consists of sensors, wireless transmission channels, sink nodes and an information processing centre. The information processing centre can receive all kinds of data collected by various sensor nodes in the WSN, such as temperature, humidity, sound, light and position. In WSN, different abnormal values represent different fault types, which affect the accuracy of data fusion. Therefore, it is crucial to research fault diagnosis methods for data streams in WSN that can detect and correct the fault node of the sensor in time to guarantee the accuracy of data fusion.

The aspects of WSN faults can be discussed below :

1) Network-level faults cause unreadable data in the fault area. It consist of connection failure, channel congestion, asynchronous clocks, illegal intrusion.

2) Hardware-level faults are common when the hardware of a sensor is damaged. Hardware damage generally appears in a power supply, memory, processor, wireless communication, etc., that causes the ability of the damaged sensor to completely fail so that sensor readings cannot be obtained.

3) Software-level faults occur due to the degradation of a sensor, which produces abnormal values. It consist of drift, precision decline, fixed bias and complete faults. The data collected in the data processing center will contain the abnormal values generated by a sensor fault.

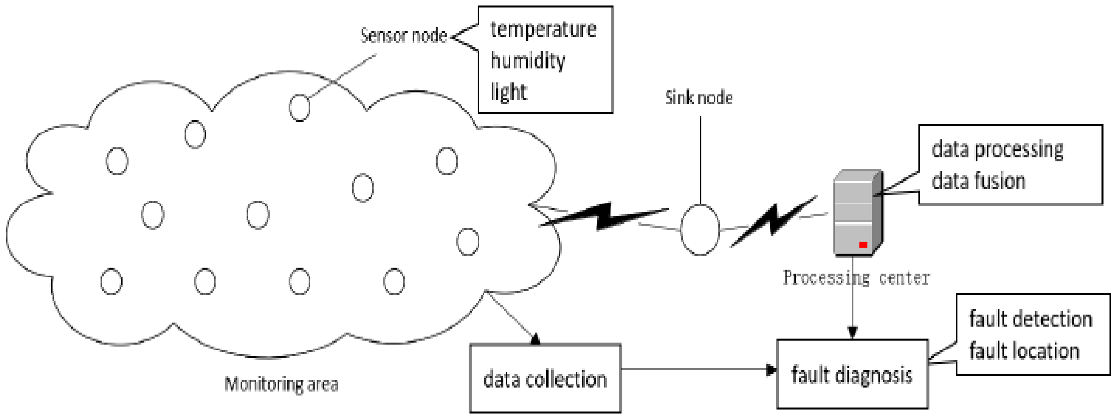

Fig: 1 WSN Basic Structure Diagram

A typical WSN consists of four parts: sensor node, wireless transmission channel, sink node and information processing center. Collection of different types of environmental data is carried out by the wireless sensor node is used for. The wireless transmission channel is used for data communication between different nodes. The sink node is used to detect the connection between the area and the external network. The processing center summarizes data sent by different sensors and processes data. The data from all the sensor nodes is collected in the data processing center of WSN. By analyzing the sensor data, abnormal values can be detected, and the faults can be diagnosed in WSN.

For fault diagnosis, three assumptions used in this paper are as follows.

1) The outputs of the system are $y(t)$ and $y(t)$. $y(t)$ is the result of the abnormality judgment of the sensor, including normal and abnormal results. $y(t)$ is the type of sensor fault, which includes normal, drift fault, precision decline fault, fixed bias fault and complete fault.

2) $X_n^m(t)$ is a fault detection dataset that contains input information for all sensors. It can be described as:

$$X_n^m(t) = \begin{pmatrix} x_1^1(t) & \cdots & x_2^1(t) \\ \vdots & \ddots & \vdots \\ x_1^m(t) & \cdots & x_n^m(t) \end{pmatrix}$$

where $x_n^m(t)$ denotes the *nth* type of data received in the m^{th} sensor at time t.

3) $A_i^m(t)$ is a dataset of antecedent attribute for sensor determination of fault type. Through the feature extraction of $X_m^n(t)$, the attribute information that reflects the different sensor fault types can be obtained and described as:

$$A_i^m(t) = \begin{pmatrix} a_1^1(t) & \cdots & a_i^1(t) \\ \vdots & \ddots & \vdots \\ a_1^m(t) & \cdots & a_i^m(t) \end{pmatrix}$$

where $a_i^m(t)$ denotes the value of the i^{th} antecedent attribute in the m^{th} sensor at time t.

Fault diagnosis consists of two parts: fault detection and determination of fault type. The two tasks are described as follows.

A.FAULT DETECTION

The aggregated data can be analyzed directly in the data processing center, and the faulty sensors can be found. Thus, the fault detection process that receives sensor data at time t can be described as:

$y(t) = f(Xm^n(t), R)$

where $f(.)$ denotes the conversion process from sensor data to fault detection results. R denotes the set of parameters in the conversion process.

B. DETERMINATION OF FAULT TYPE

It is difficult to directly apply the acquired information to sensor determination of fault type. Hence the features in the sensor data and the corresponding antecedent attributes should be captured. Thus the determination of the fault type process of the sensor at time t can be described as:

$y(t) = g(\mathrm{A}_m^i(t), \mathrm{n})$

3.RELATED WORKS

Wireless Sensor Networks (WSNs) have played an important role in information collection and monitoring solution for a variety of applications. Faults occurrence in sensor nodes are common due to the sensor device itself and the change in environment where the sensor nodes are deployed. To ensure the network quality of service it is important for the WSN to be able to detect the faults and take actions to avoid further deployment of the service. The goal of this paper is to locate the faulty sensors in the wireless sensor networks hence a localized fault detection algorithm is used to identify the faulty sensors. By the use of this technique, implementation complexity of the algorithm is low and the probability of correct diagnosis is very high even in the existence of large fault sets [1].

A new technique called generic rule-base inference methodology using the evidential reasoning (RIMER) approach is proposed. First Existing knowledge-base structures are examined, and the knowledge representation schemes under uncertainty are briefly analyzed. A new knowledge representation scheme in a rule base is proposed using a belief structure, based on this analysis. A rule base is designed with belief degrees embedded in all possible consequents of a rule, in this scheme. Such a rule base is capable of capturing vagueness, incompleteness, and nonlinear causal relationships, rather traditional if–then rules can be represented as a special case. Investigation of other knowledge representation parameters such as the weights of both attributes and rules are also done in this scheme. An input to an antecedent attribute is transformed into a belief distribution, in an established rule base. Hence, inference in such a rule base is implemented using the evidential reasoning (ER) approach [2].

Addition of cognition to the existing Wireless Sensor Networks (WSNs) , or usage of numerous tiny sensors. CWSNs allow the current WSNs to overcome the scarcity problem of spectrum which is shared with many other successful systems such as Wi-Fi and Bluetooth. Also, cognitive technology could provide access not only to new spectrum, but also to spectrum with better propagation characteristics. Thus different data rates can be achieved, by the adaptive change of system parameters such as modulation type and constellation size, which in turn can directly influence the power consumption and the network lifetime. Furthermore, sensor measurements obtained within the network can provide the needed diversity to cope with spectrum fading at the physical layer [3].

A distributed model-based fault detection algorithm is used which is based on local pair-wise verification, there exists a linear relationship between the outputs of any pair of sensors. Therefore, the relationship between a pair of sensors can be modelled by a linear model , by partitioning the network into sensor pairs. Again with the detection of general faults happened within a sensor pair, an algorithm for identifying non-linearity type of fault without the use of reference sensors was also developed. Communication power is also greatly reduced by the distributed nature of the algorithm [4].

Prediction of both observable and hidden behaviours in complex engineering systems is an important thing. It is often difficult to establish a forecasting model for hidden behaviour when compare with observable behaviour. The belief rule base (BRB) has been employed to predict the observable behaviour using the hybrid information with uncertainties, but it is still not applicable to predict the hidden behaviour directly. Thus a new BRB-based model is proposed to predict the hidden behaviour. The initial values of parameters are usually given by experts, in the proposed BRB-based model, thus some of them may not be accurate, which may lead to inaccurate prediction results. In order to solve the problem, on the basis of maximum likelihood algorithm a parameter estimation algorithm for training the parameters of the forecasting model is further proposed. By using the hybrid information with uncertainties, the proposed model can combine together with the parameter estimation algorithm and improve the forecasting precision in an effective manner [5].

For key performance indicator (KPI) monitoring in large-scale process industry, Standard partial least squares (PLS) serves as a powerful tool since two decades. However, the standard approach and its recent modifications still experience some problems for fault diagnosis related to KPI of the underlying process. To subsist with these difficulties, an improved PLS (IPLS) approach is developed. IPLS is able to disintegrate the measurable process variables into the KPI-related and unrelated parts, respectively. To offer meaningful fault diagnosis information, the corresponding test statistics are developed based on it and thus the corresponding maintenance actions can be further taken to ensure the desired performance of the systems [6].

Particle filter (PF) provides a kind of particular novel technique for approximating the hidden states of the nonlinear and/or non-Gaussian systems. However, the general PF always suffers from the particle destituteness problem which can lead to the false state estimation results. To manage with this problem, an improved particle filter, i.e. intelligent particle filter (IPF), is implemented in this paper. It is inspired from the genetic algorithm. The particle impoverishment in PF is mainly due to poverty of particle diversity. In IPF, the genetic operators based strategy is developed to further modify the particle diversity [7].

It is difficult to assess the lives of newly modified products by using failure data from various testing environments. Currently, two steps are generally included. The first step is converting the failure data under one testing environment into the actual working environment, and the second step is merging all failure data under the actual working environment into a unified result. Thus most available methods cannot use information that includes part failure data and part expert knowledge simultaneously. To overcome the above issue, a new BRB-ER-based model is proposed, based on the belief rule base (BRB) and the evidential reasoning (ER) approach, where the BRB is used to transform the failure data from one testing environment into the original working environment. The ER approach, is used to assess the life of a product , which is adopted to aggregate the failure data from different testing environments. The BRB-ER-based model is applied to represent and integrate asynchronous multisource information is the conclusion. The initial BRB system is developed on the basis of experts' knowledge in the proposed model, which results in uncertainty because of the ambiguous nature of human judgment and calls for training the parameters in the BRB-ER-based model. However, an optimal algorithm that employs the differential evolutionary algorithm is proposed. Both the proposed model and the optimal algorithm operate in an integrated manner in order to improve the assessment precision by using both failure data and expert knowledge effectively [8].

By taking into account the current state, it is dangerous to online assess the safety of a complex dynamic system degradation trend, and historical records together. A new safety assessment model with an online algorithm based on the evidential reasoning (ER) approach is proposed. It not only take into account the relative importance of each safety indicator, but also consider the reliability of each indicator. To achieve the integrated safety level, multiple safety indicators are fused at first and the "history," "current," and "future" safety states are then integrated. Initially, a forecasting model based on the third order Volterra filter is proposed to predict the safety indicators' information online.
Secondly, an adaptive weighting model is developed to automatically adjust to various conditions and track the characteristics of the dynamic system, and the reliability of each indicator is considered to destroy the influence of inherent disturbance and/or noise. At last, a safety assessment aggregation scheme based on the ER approach is presented to merge the history, current, and future safety indicators to obtain the corresponding safety state, and the safety states are then fused synthetically to obtain a comprehensive safety assessment result of the complex dynamic system [9].

Prediction of the hidden behaviour of a complex system is very important. For predicting the hidden behaviour, the hidden belief rule base (HBRB) is an effective model which can use qualitative knowledge and quantitative data, in the existing models. The completion of the frame of discernment (FoD) of HBRB which is composed of some states or propositions and the universal set including all states or propositions is not done. consideration of both the global ignorance and local ignorance cannot be possible at the same time, which

may lead to the inaccurate forecasting results. To solve the problems, a new HBRB model named as PHBRB in which the hidden behaviour is described on the FoD of the power set is proposed. Furthermore, by using the evidential reasoning rule as the inference tool of PHBRB, a new projection covariance matrix adaption evolution strategy is developed to optimize the parameters of PHBRB so that more accurate prediction results can be obtained [10].

In wireless sensor network (WSN), wireless sensor fault diagnosis based on fusion data analysis has attracted attention in the wireless sensor field. Detection and correction of the faults of sensor nodes is performed in time to improve the accuracy of sensor data fusion. In the current paper, the data characteristics of WSN are analysed, and a method is proposed for fault diagnosis of WSN based on a belief rule base model. First, the sensor fault diagnosis process is described on the basis of characteristics of a wireless sensor in WSN. Then, the characteristics of sensors are analysed from the aspects of time, space, and attributes. Finally, based on the hierarchical BRB model a fault diagnosis model is proposed. To make the results more accurate, a covariance matrix adaptation evolution strategy algorithm is used to optimize the initial parameters of the proposed model [11].

4.MODIFICATION

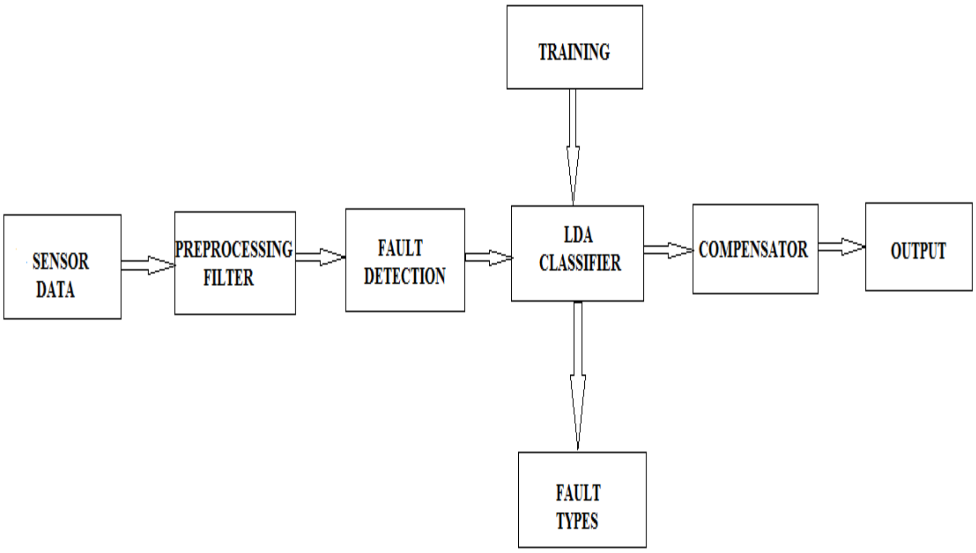

Fig2 : Block diagram of modified system

SENSOR DATA:

Sensors collect all kinds of data such as temperature, humidity, sound, light and position. The data collected by the sensor nodes will contain the abnormal values generated by a sensor fault.

Based on characteristics of abnormal values the five fault types are:

1. Stuck at fault
2. Offset fault
3. Gain fault
4. Out of bounds fault
5. Data loss fault

1. Stuck at fault : This fault is happened when the variation of sensed data series is zero, which can either be transient or persistent. Fault simulators and automatic test Pattern Generation tools uses fault model to mimic a developing defect inside an integrated circuit. Assumption is made that a fault in a logic gate results in one of its inputs or the output being fixed to either a logic 0 (stuck- at- 0) or a logic 1 (stuck- at -1). It is also abbreviated as s-a-0 and s-a-1 respectively.
2. Offset fault : This fault occurs when a constant is added to the expected data , which can happen due to bad caliberation of sensing unity.
3. Gain fault : This sort of fault is happen when in a period of time , the change rate of sensed data is different to the expectation .
4. Out of bounds fault : Let [$Ø_1$,$Ø_2$] an interval describing the possible normal value of a type of data . An out of bounds fault happens when for a sensed data x € f(t) such that
   $x < Ø_1$ or $x > Ø_2$.

5. Data loss fault : This type of fault can be simply described by the fact of “ The missing of data during a time series for a node “. This means that the sensed data is a null value.

FAULT DETECTION :

Comparing normal and abnormal data, fault detection of the sensor is achieved. In the comparison process, sensors are classified by clustering. Each sensor node is compared with other nodes. If the current sensor node data are obviously different from the other nodes in a certain period of time, the different value accumulated in the sensor is exceeded when a preset threshold is presented.

Table 1: The results of clustering

Cluster	Sensor node
1	1 2 3 4
2	6 7 8 9 10
3	11 12 13 14 16
4	17 18 19 20
5	21 22 23 24 25
6	26 27 28 29 30 31 32
7	33 40 41 42 43
8	34 35 36 37 38 39
9	44 46 47 48 49 50 51 52
10	53 54

DATA CORRELATION CHARACTERISTICS OF SENSORS

Some data correlations can be determined by analysing the working principles of sensors in the WSN, such as the following three characteristics.

1) Time correlation: information collected over a small interval of time represents similar adjacent sensor information.

2) Space correlation: in the monitoring area, due to the limitation of communication distance between wireless sensors, the small distance between the sensors causes similar information in adjacent sensor nodes.

3) Attribute correlation: the sensor will collect a variety of different types of information; usually, there are correlations of environmental data, such as temperature and humidity. When the data processing center receives all the data collected by the sensor, the need for data correlation still exists. Therefore, in fault diagnosis, the antecedent attributes are extracted based on data correlation.

a) The attributes based on time correlate with a time interval. The characteristics of the data are analysed within this time interval, and the antecedent attribute of time correlation is extracted.
b) The attributes based on space correlation: the sensor clusters are established by clustering sensors. The antecedent attribute of space is extracted by data comparison between the current sensor and other sensors in the cluster.

c) The attributes based on attribute correlation: Through the comparative relationship of attributes, the antecedent of an attribute is extracted.

FEATURE EXTRACTION :

Using Feature extraction values the fault can be classified .The extracted correlation features is based on Space ,Attributes and Time and fourier transform. Each parameter used to differentiate the fault correlation values. The correlation parameters are Mean, mean square, Variance, skewness, Kurtiosis, proportion Correlation coefficient standard deviation. Its all based on time, space and attributes based

LDA CLASSIFIER

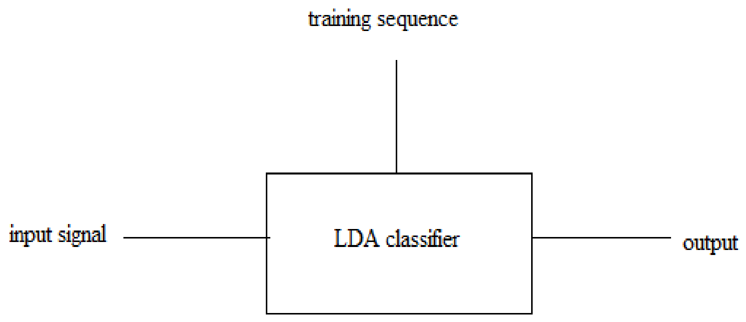

Fig 3: Block diagram of LDA classifier

Here each of the input sequence is compared with the training sequence and a particular value is obtained. Among these values obtained, the minimum value is selected and thus according to the value, the assigned fault is detected.

Moving weighted average method is used for the compensation, this describes that windows are placed on graph and the values of the peak is calculated from that the average is obtained and thus the fault is compensated.

A preprocessor is used before the fault detection in order to eliminate the noise containing in the sensor node.

5.RESULT

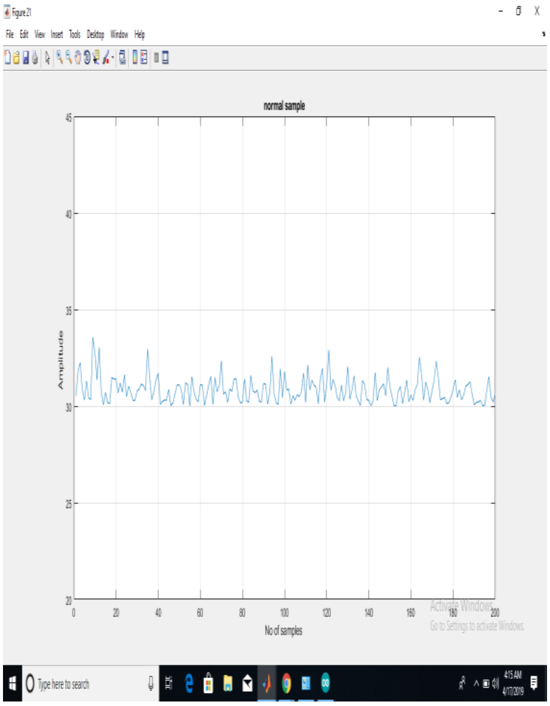

Chart 1: temperature sensor input

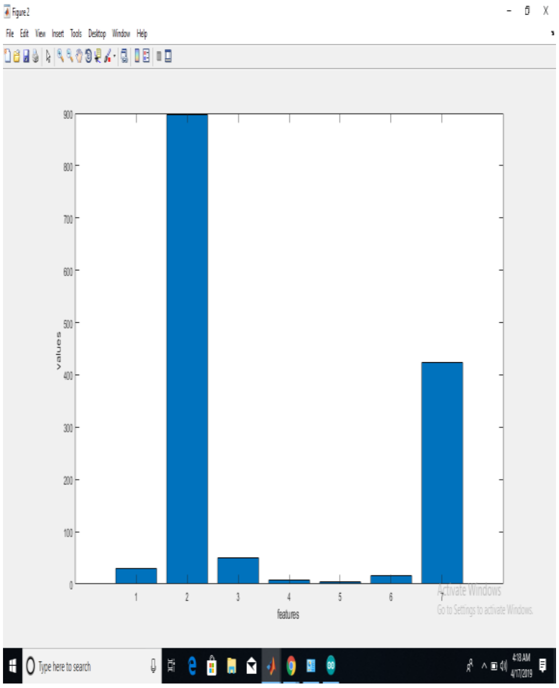

chart 2: feature of the sensed values

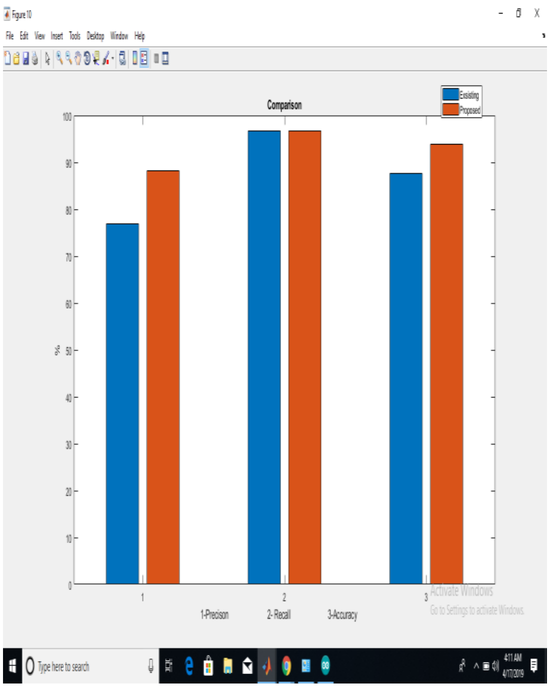

Chart 3: comparison between

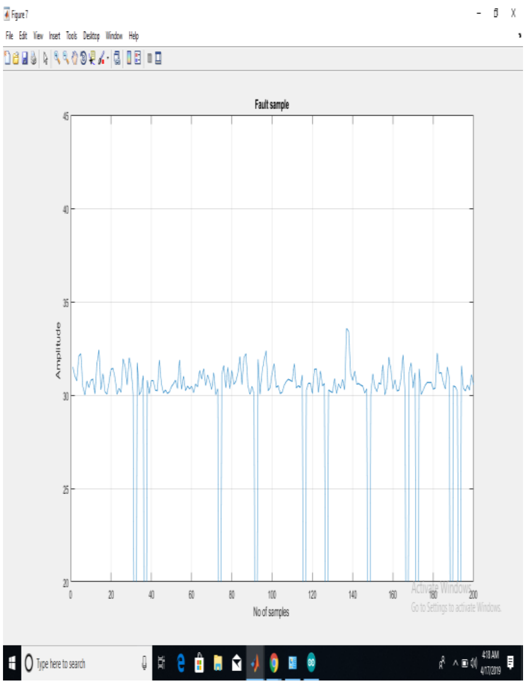

chart 4: fault occurred in the sensed data

3. CONCLUSIONS

In wireless sensor network (WSN), wireless sensor fault diagnosis based on fusion data analysis has provided attention in the wireless sensor field. Detection and correction of the faults of sensor nodes in time is performed to improve the accuracy of sensor data fusion. First, the sensor fault diagnosis process is described on the basis of characteristics of a wireless sensor in WSN. Then, the characteristics of sensors are analyzed from the aspects of time, space, and attributes. Random fault can be detected. In order to detect the fault types Linear discriminant classifier can be used and also the type of fault is displayed along with the graph .Fault compensator will be used to stabilize the faulted data i.e moving weighted average method is used to compensate the high peak values . Along with the time, space, attribute correlation here Fourier transform parameters are also used.

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